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ELECTRONIC PRODUCTIVITY PERFORMANCE MONITORING OF CONSTRUCTION WORKERS

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Thesis

PH.D. CIVIL ENGINEERING — CIVIL CONSTRUCTION

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To my Family and Friends

My deepest fear is not that of not arriving, but that of not departure.

Amyr Klink

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ABSTRACT

The Construction Industry (CI) is failing to boost its productivity. Moreover, 56% of the industry employment is craft workforce. This statistic means that increasing craft workforce productivity introduces positive impacts on overall construction productivity. The topic is relevant for many constituents from Government to the Companies level. The lack of craft workforce available in developed countries and the CI increasing requirements towards higher productivity and efficiency imply these agents' actions.

The research frames specifically the craft workforce performance as the problem to be solved in the CI productivity scenario. Many authors have worked on the construction productivity theme (e.g. assessment levels, processes analysis, impact factors). Also, human activities recognition/classification applying sensing technology and automated processing have being experienced nowadays. This work combines both contributions to produce the outcomes that will provide the opportunity to boost on-site productivity. Higher competitiveness and efficiency are goals for the construction industry. Construction 4.0 is a megatrend and a driver towards those objectives. There is a gap between the relevance of the craft workforce for overall productivity and the investment in actions to measure and improve that productivity. In a 4.0 context, this gap tends to increase as low technology is invested in craft workers. This work highlights the relevance of the craft workforce on the overall industry and forecasts how a 4.0 vision targeted for these agents can decrease the gap mentioned above.

The thesis main aim is to develop a framework to measure craft workforce productivity. Being the objectives: Conceptualise an approach to assess and modelling craft workforce productivity; Provide in-depth knowledge to enable GDPR (General Data Protection Regulation) compliance; Conceptualise the Electronic Performance Monitoring (EPM) data flow, connecting system/methodologies; Testing the EPM application and validation of the proposed framework.

The research is undertaken on an exploratory basis; this work "mix and match" methods to better achieve the particularities of this construction management research. This work combines new approaches for the CI to achieve 4.0 era using a well-known methodology for motion study (that had little experimentation in this sector) and innovative processes for data collection (wearables sensing technology) and processing (machine-learning and multivariate statistical analysis to classification). Ten construction activities were simulated in laboratory facilities performed by six volunteers using wearables to collect the acceleration (two wrists and one leg) and applying machine-learning plus multivariate statistical analysis for post-processing. In addition, data were collected on-site (through work sampling) to measure and model two production processes typical of civil construction. Craft workers also carried out wearable electronic devices to collect their reactions to EPM through interviews. A survey containing twenty-five questions was proposed for collecting managers-level awareness about EPM at the workplace. Experts semi-structured interviews from three different countries were used to capture the conceptualisations and challenges regarding Worker 4.0 in the CI. The primary outcome is a framework to model work processes and measure productivity. Craft performance modelling can bring awareness about the on-site tasks mechanization processes fostering productivity improvements.

The research provides in-depth knowledge to enable GDPR compliance based on 18 packages of agreements. Also, conceptualise an EPM data flow, connecting system/methodologies. Based on the survey, an expressive level of 56% EPM acceptance was determined, and surprisingly 69% of the respondents first knew about EPM through the survey. An approach to assess and modelling craft

workforce productivity was conceptualised as Worker 4.0 Motion Productivity (Contenting nine processes: Free-hand performing, Auxiliary tools, Manual tools Electric/Electronic tools, Machines operation, Robotic automation, Do not operating value, Walking, Carrying); Worker 4.0 Flow to boost Productivity (Efficiency flow connecting the nine processes and accounting for the amount of performance on each; plus a Mechanization index level calculated based on the process modelling); Worker 4.0 Mapping chart (Two-hand methodology to be fulfilled based on an EPM system).

The results applying EPM in the laboratory circuit for three IMUs (both wrists and one at the dominant leg) achieve accuracy between 92-96% for Machine-learning processing and 47-76% for the Multivariate statistical analysis approach. And, for one IMU (only wrist-dominant data), 32-76% accuracy for Multivariate statistical analysis approach. On-site experiments collecting data from three activities were performed, resulting in the modelling of the processes and fulfilling the Worker 4.0 Flow to boost productivity, achieving: Water supply system (to consumers' taps) a Mechanization index of 42.20% considered High in the scale proposed; Masonry (residential building with expanded clay blocks) a Mechanization index of 15.69% considered Low in the scale proposed; Masonry (commercial building with expanded clay blocks and concrete blocks) a Mechanization index of 13.64% considered Low in the scale proposed.

Due to the restrictions imposed by the world pandemic of COVID-19, it was impossible to carry out further experiments. Such restrictions limited the development of the work. In the electronic monitoring field, only ten activities were catalogued among four of the nine idealised processes. It was also not possible to process data collected on-site electronically. To meet the need for process modelling, it was only possible to develop analyses at three different construction sites using a work sampling methodology. As a result, the amount of data/results was only limited to masonry and piping activities. It was impossible to perform any tests to validate the Worker 4.0 Mapping chart concept, nor was it possible to supply any KPIs identified with collected data.

The contribution to knowledge for theoretical implication includes the conceptualisation of a framework craft-workforce-centred focusing on the modelling of construction activities. The practical use of a quantitative Mechanization index can lead to a benchmarking of activities prone to delivering the highest levels of outcomes and increase CI productivity. The future direction of this work should focus on expanding on-site data collection. It should also seek to establish algorithms for automating data processing.

KEYWORDS: Construction 4.0; Project Management; Craft workforce; Personal Data Protection; Modelling Motion Productivity.

RESUMO

A Indústria da Construção (IC) não têm conseguido de forma satisfatória aumentar sua produtividade. Com destaque, 56% do emprego na IC é relativo à mão de obra direta. Com isto, o aumento da produtividade da força de trabalho em estaleiros apresentará impactos positivos na produtividade geral da construção. O tópico é relevante tanto para o governo quanto para as empresas.

Este trabalho enquadra especificamente o desempenho da força de trabalho em estaleiro como o problema a ser resolvido no cenário de produtividade dentro da IC. Muitos autores têm trabalhado no tema da produtividade da construção (e.g., níveis de avaliação, análise de processos, fatores de impacto). Além disso, o reconhecimento/classificação de atividades humanas aplicando tecnologia de sensoriamento e processamento automatizado têm sido alvo de pesquisas científicas. Maior competitividade e eficiência são metas para a construção civil. A Construção 4.0 é uma megatendência e um impulsionador desses objetivos. Existe uma lacuna entre a relevância da força de trabalho direta para a produtividade dos projetos e o investimento em ações para medir e melhorar dessa produtividade em obra. Em um contexto 4.0, essa lacuna tende a aumentar à medida que pouca tecnologia é investida na avaliações dos processos das tarefas em estaleiros.

O objetivo principal da tese é desenvolver uma estrutura para medir a produtividade da força de trabalho direta. Sendo os objetivos: Conceituar uma abordagem para avaliar e modelar a produtividade da força de trabalho direta; Fornecer um conhecimento profundo para permitir a conformidade com o GDPR (*General Data Protection Regulation*); Conceituar o fluxo de dados do Monitoramento Electrónico de Desempenho (EPM - *Electronic Performance Monitoring*), conectando sistema/metodologias; Testar a aplicação de EPM e realizar validação do framework proposto.

A pesquisa é realizada de forma exploratória; este trabalho "mistura e combina" métodos para melhor atingir as particularidades desta pesquisa em gestão da construção. Este trabalho combina novas abordagens para o CI atingir a era 4.0 usando uma metodologia bem conhecida de estudo de movimento (que teve pouca experimentação neste setor) e processos inovadores de coleta de dados (tecnologia baseada em *wearables*) e processamento (aprendizado de máquina e estatística multivariada para classificação). Dez atividades de construção foram simuladas em instalações de laboratório e realizadas por seis voluntários vestindo *wearables* para coletar a aceleração (dos dois pulsos e de uma perna) e, aprendizado de máquina e análise estatística multivariada para pós-processamento. Além disso, foram coletados dados em obra (por meio do método de amostragem) para medir e modelar dois processos produtivos típicos da construção civil. Dispositivos electrónicos vestíveis também foram utilizados por trabalhadores da mão de obra direta para coletar suas reações ao EPM por meio de entrevistas. Uma pesquisa contendo vinte e cinco questões foi proposta para coletar a perceção dos gerentes sobre a EPM no local de trabalho. Entrevistas semiestruturadas com especialistas de três países diferentes foram usadas para capturar as conceituações e os desafios relacionados ao Worker 4.0 na CI. O resultado principal é uma estrutura para modelar processos de trabalho e medir a produtividade. A modelagem das tarefas pode trazer consciência sobre os processos produtivos, promovendo melhorias da produtividade.

A pesquisa fornece conhecimento profundo para permitir a conformidade com o GDPR com base em 18 pacotes de contratos. Além disso, conceitualiza um fluxo de dados EPM, conectando sistema/metodologias. Com base num inquérito, um nível expressivo de 56% de aceitação de EPM foi determinado e, surpreendentemente, 69% dos entrevistados souberam da EPM pela primeira vez por meio da pesquisa. Uma abordagem para avaliar e modelar a produtividade da força de trabalho direta

foi conceituada como *Worker 4.0 Motion Productivity* (contendo nove processos); *Worker 4.0 Flow to boost Productivity*; *Worker 4.0 Mapping chart*. Os resultados da aplicação de EPM no circuito de laboratório para três IMUs (ambos pulsos e um na perna dominante) alcançam precisão entre 92-96% para o processamento de aprendizado de máquina e 47-76% para a abordagem de análise estatística multivariada. E, para um IMU (apenas dados de pulso dominante), precisão de 32-76% para abordagem de análise estatística multivariada. Foram realizados experimentos em obra coletando dados de três atividades, resultando na modelagem dos processos e preenchendo o Fluxo do Trabalhador 4.0 para aumento de produtividade, alcançando: Sistema de abastecimento de água um Índice de Mecanização de 42,20% considerado Alto no escala proposta; Alvenaria (edifício residencial com blocos de argila expandida) Índice de mecanização de 15,69% considerado Baixo na escala proposta; Alvenaria (edifício comercial com blocos de argila expandida e blocos de concreto) Índice de mecanização de 13,64% considerado Baixo na escala proposta.

Devido às restrições impostas pela pandemia mundial de COVID-19, foi impossível realizar novos experimentos. Tais restrições limitaram o desenvolvimento da pesquisa. No campo da monitorização electrónico, apenas dez atividades foram classificadas. Também não foi possível processar os dados coletados eletronicamente nas obras. Para atender à necessidade de modelagem de processos, só foi possível desenvolver análises em três diferentes canteiros de obras utilizando uma metodologia de amostragem de dados. Como resultado, a quantidade de dados/resultados foi limitada apenas às atividades de alvenaria e tubulação de água. Não foi possível realizar nenhum teste para validar o conceito do *Worker 4.0 Mapping chart*, nem abstecer com dados quaisquer KPIs identificados.

A contribuição para o conhecimento e a implicação teórica deste trabalho inclui a conceptualização de um *framework* centrado na mão de obra direta com enfoque na modelação das atividades de construção. O uso prático de um índice de mecanização quantitativo pode levar a um *benchmarking* de atividades propensas a entregar os mais altos níveis de resultados e aumentar a produtividade da IC. A direção futura deste trabalho deve se concentrar na expansão da coleta de dados em obra. Deve também, procurar estabelecer algoritmos para automatizar o processamento de dados.

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LIST OF SYMBOLS, ACRONYMS AND ABBREVIATIONS

3D - three-dimensional computer graphics

4D - is related to planning the construction site by adding a new element i.e. time

5D - is related to planning the construction site by adding a new element i.e. cost

5W2H - Who, What, Where, When, Why, How, How much

AdB - AdaBoost

ANN - Artificial neural network

AI - Artificial Intelligence

AIG - American international group

AREA - Anticipate, reflect, engage, act

Art. - Article

AUT - Auxiliary tools

BIM - Building information modelling

BREEAM - Building research establishment's environmental assessment method

CAR - Carrying

CASBEE - Green star and comprehensive assessment scheme for built environment efficiency

CCTV - Closed-circuit television

C-LRF - Crew labour rating factor

CI - Construction industry

CICCOPN - *Centro de Formação Profissional da Indústria da Construção Civil e Obras Públicas do Norte*

CII - Construction industry institute

COBie - Construction Operation Building information exchange

CPM - Critical path method

DEA - Data envelopment analysis

DOC - Document

DPIA - Data protection impact assessment

DPO - Data protection officers

DT - Decision tree

EAM - Environmental assessment methods

ECG - Electrocardiogram

EEA - European economic Area

EEG - Electroencephalogram

EET - Electric/Electronic tools

EU - European Union

EPC - Engineering, procurement and, construction

EPM - Electronic performance monitoring

EPSRC - Engineering and physical research council

ERP - Enterprise resource planning

ExT - Extremely randomized trees

FHP - Free-hand performing

FIS - Fuzzy inference systems

GDP - Gross domestic product

GDPR - General data protection regulation

GHG - Greenhouse gases

GL - Guidelines

GNSS - Global navigation satellite system

GPS - Global positioning system

GrB - Gradient boosting

HBP - Human brain project

JRC - Joint research centre

KNN - K-Nearest neighbours

KPI - Key performance indicator

LCA - Life cycle assessment

LEED - Leadership in energy and environmental design

LR - Logistic regression

LRF - Labour rating factor

LSVM - Linear support vector machines

M.h - Man-hour

MLP - Multilayer perceptron

MNT - Manual tools

MOP - Machine operation

IMU - Inertial measurement unit

IDL - Do not operating value

IEEE - Institute of electrical and electronics engineers

IoT - Internet of things

ISO - International organization for standardization

IT - Information technology

UAV - Unmanned aerial vehicle

UK - The United Kingdom

USA - The United States of America

UWB - Ultra-wide-band

Q - Quartiles

PDCA - Plan, do, check, act

PERT - Project evaluation and review technique

PORE - Point of registration for ethics concerns

PPE - Personal protective equipment

PPG - Photoplethysmography

PSVM - Polynomial support vector machines

RBA - Robotic automation

Rec. - Recital

RF - Random forest

RFID - Radio-frequency identification

RII - Relative importance index

ROI - Return on investment

RSVM - Radial basis function support vector machines

SME - Small and medium-sized enterprises

SSVM - Sigmoid support vector machines

SVM - Support vector machines

Vote - Majority/Hard Voting

W4MP - Worker 4.0® motion productivity

WD - Worker dimension

WBS - Work breakdown structure

WLK - Walking

WP - Working party

1
INTRODUCTION

1.1 INTRODUCTION

The construction management research field is perhaps as diversified and complex as the nature of the construction industry itself [1]. Research work in this field faces several risks, and in most cases, it has limited resources [1]. An external risk, resulting from the world pandemic of COVID-19, generated constraints for the entire planet, and nevertheless, had an impact on the development of the methodologies predicted in this work.

Over the years, CI has faced difficulties in increasing its productivity. Even more in this moment of the global pandemic, the need to digitise the sector to achieve a higher performance index has become evident [2]. This work aims to contribute to deepening knowledge in the area of productivity management, with a particular focus on the craft workforce. In this study, research is used as a means to assist stakeholders in the area of a project and human resource management and in the decision-making process. Due to constraints inherent in the research area and unpredictable constraints, this work "mix and match" methods to better achieve the particularities of this development [3–5]. This chapter presents the work motivation, a brief context of the CI actual scenario, and the thesis objective and method.

1.2 THE MOTIVATION

Over the last two decades, the Construction Industry (CI) has been facing low productivity growth [6]. The fourth industrial revolution is starting to be a global reality. Other sectors as Manufacturing are 4.0 champions and increasing their productivity faster [6–10]. The CI is heterogeneous and complex issues make "ready-made" solutions unfeasible, for example, geological differences, clients' regional needs, and the human and material resources available where the building takes place [11–16]. The Construction Industry is heterogeneous and complex and will remain elementary a craftmanship as it will always need skilled human labour. Productivity growth challenge will demand a series of innovative on-site solutions. Beyond that, each improvement vector will increment the productivity in CI. As a result, what motivates this work is this search; it is to try to develop vectors that may help solve this productivity complex problem. Within this vision, specific challenges stand out:

- The primary concern is low productivity in the construction industry [17];
- The bottleneck in implementing electronic performance monitoring is data protection regulation and people's reactions [18];
- The challenge is data information flow by different systems to many stakeholders [19];
- The barrier to increasing productivity sits on performance data manual collection and processing [8];
- There is a gap in methods of productivity performance modelling and measuring for the construction tasks.

1.3 THE CONSTRUCTION INDUSTRY

The construction industry is a significant player in the world economic scenario, as construction-related spending accounts for 13% of the global GDP [6]. The weak productivity growth in construction is a global phenomenon [7]. Construction productivity has barely increased by 1% a year since 1997 [6]. According to Farmer (2016) in the next decade, the UK could suffer a 20-25% decline in the available labour force. That workforce shrinkage should be mitigated with innovation to boost labour productivity in the construction sites [7].

At the European Union level, construction "crafts and trade workers" accounts for 56% of sector' employment [17]. According to Mojahed and Aghazadeh (2008), in the context of the construction engineering, productivity is mainly related to the performance achieved within each work activity that to make up an enterprise [20]. The central concept of productivity in the CI is related to a measured ratio of inputs efficiently converted by tasks into tangibles outputs [21–23]. Overall project performance is also assessed, through aspects such as cost, schedule, quality, and safety. In order to compare enterprises' self and cross performance, it is necessary to establish principles of data collection and treatment to achieve reliable KPIs and benchmarking.

The assessment of productivity to increase the performance of projects is not a one-time job [21]. The systematic control of construction operations brings immediate awareness of specific aspects of the activities under development to provide the needed information for decision-making within an agile management environment [24]. Current technological advances enable new methods of data collection that increase reliability and real-time information. Also, recent innovations in micro and nanotechnology allow for the sustained assessments of the each worker's task performance on-site.

1.4 CONSTRUCTION 4.0

The fourth industrial revolution (4.0 cycle) raises several concerns about friction between humans and technology use. All the economic sectors are coming into the 4.0 cycle [25–31], and the construction industry cannot be an exception [32].

According to McKinsey (2017), the construction industry has an economic opportunity of 1.6 trillion American dollars a year and must follow the manufacturing industry's example and invest heavily in technology [6]. The Industry 4.0 concept aims at complete information (IoT) for digitalization and works automation. In the construction industry (CI) context, task processes remain firmly linked to the craft workforce.

The trends towards Construction 4.0 suggest the increased involvement of digitalization and automation. There is an increased relevance of monitoring as the human craft workforce is the industry's primary productive force; therefore, it constitutes an important research topic. Also, tasks with a higher level of mechanization achieve more significant output indexes [33]. Organizations are naturally interested in monitoring the performance of their workers [34]. Monitoring employee performance allows companies to evaluate their return on investment [34,35]. Monitoring also allows supervisors to obtain important information for application in workforce development. Thus, organizations have been monitoring their employees for centuries [36]. According to Stoney (2001), technological advances in the electronic area are transforming the way in which workers' performance is measured [35], being it nominated as (EPM) Electronic Performance Monitoring [36,37].

The future role of construction craft workforce will pass through: Electronic Performance Monitoring (EPM), BIM integrated Smart Contracts and Artificial Intelligence (decision-making) [38]. One of the biggest challenges of implementing machine-controlled systems is to create environments that are ethically delegated by pre-established collective-agreements rules, GDPR compliant and, at the forefront, the awareness and consent of each worker [38].

Regarding the work routines at construction sites, two main vectors of innovation can be highlighted. Namely, electronic performance monitoring (digitalization) and efficiency increase through the employment of tools, machines, and equipment (mechanization/robotization). Hwang et al. 2019 emphasize that the measurement of mechanization of tasks performed by construction workers is vital [33]. Increasing mechanization on-sites boosts productivity and may mitigate the current lack of available craft workforce [33].

The impact of new technologies on employment and the employee's perception of fairness constitute a significant challenge [39,40]. Artificial Intelligence (AI) is a technology with a growing application within these domains as it is inspired by biological systems to make machines smartest [41]. AI-based studies on decision-making applications include topics such as: Algorithmic; Artificial Neural Networks; Decision Support Systems; Deep Learning; Deep Neural Networks; Expert Systems; and Learning Systems [18,42].

The implementation of innovations in the construction industry into the 4.0 era implies three vectors: Technology, Processes and People [43,44]. Finding the correct balance between these vectors is the success key for the identification of the roles, training needs and involvement of the persons/construction agents [45]. It is argued by some scholars such as Sujan et al. (2019) that people are more foundational to the technological and process factors [46].

Figure 1.1 frames on one side the main "traditional" requirements of the construction industry (aspects that constitute a scope for performance measurement) and on the other side the main technological drivers towards the Industry 4.0 vision. Also, in Figure 1.1, the innovation vectors are colourfully highlighted; Process (magenta), Technology (green) and, People (red). All the following pursuit this pattern and the colours are meaningful in what relates to it.

In general, in the manufacturing sector it is linked to the use of machines and continuous processes. In this context, the increase in production can be directly influenced by the automation of processes and the increase in machines that produce a large amount number of units.

On the other hand, the construction industry (mainly building construction) is characterized by the heterogeneity of tasks/projects and on-site implementation, thus making the automation of its processes more complicated. Nevertheless, construction maintains its productivity linked to the labour of human resources. Consequently, the construction industry's KPIs are most connected to workers, and, in the manufacturing industry, they are most linked to machines.

The construction-technology firms have invested $10 billion, between 2007 and 2017, in advanced software, specific hardware, and analytics capabilities [6]. According to McKinsey (2016), innovative technological solutions for the construction industry need to deliver a seamless, real-time experience [47], by field as:

- Design management, integrating 3-D models, 4D and, 5D on-site, using mobile platforms;
- Quality control, offer remote site inspection using pictures and tags;
- Scheduling, tracking progress and workers active in real-time;
- Contract management, communication of on-site information in real-time;
- Materials management, identifying and tracking materials and equipment;
- Crew tracking, providing real-time status updates of the workforce productivity.

As a result, it is needed to invest in research and technological development in the construction-technology field to boost labour productivity in order to increase companies' profits and mitigate the future tendency of the workforce shrinkage.

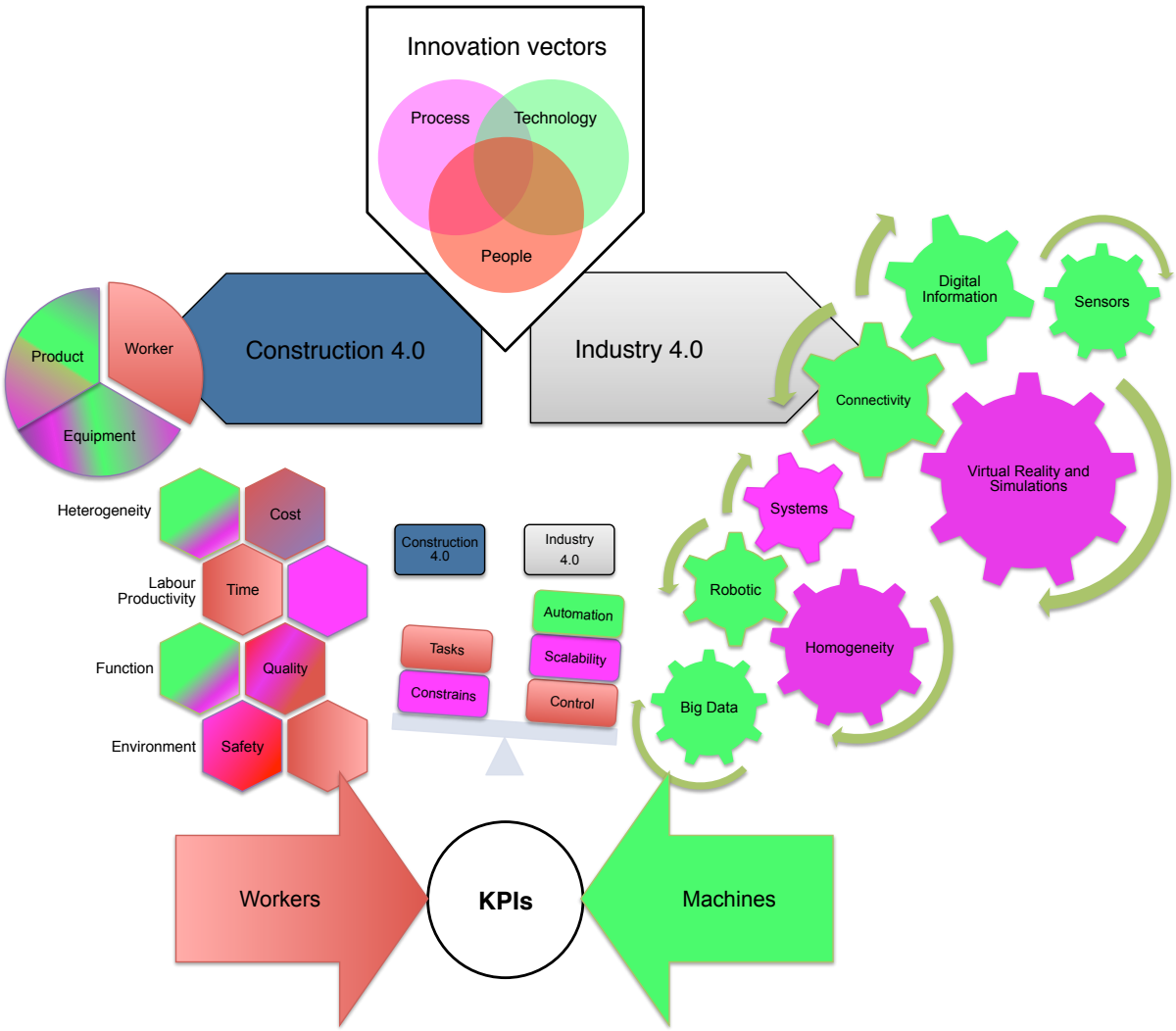


Figure 1.1 – 4.0 scenario.

Besides, the year 2020 is marked by a unique global pandemic phenomenon. In this context, companies were led to develop a large part of their work remotely [2]. Even the construction industry had to, when possible, practice teleworking. On-site construction had to stop its activities at times due to, for example, the lack of products, or cases of infection of the workforce and even governmental impositions. This unique situation reinforced the need for digitalization across the construction

industry. In the case of construction sites, several measures were necessary, such as, for example, measuring the body temperature of workers and guaranteeing a social distance between them. Many solutions to achieve these objectives have been developed based on innovative technologies as thermography and portable/wearable devices. Adding to that, very important in this time, automated data collection and processing methodologies increase control, agile the decision-making, and boost performance.

As above stated, Construction 4.0 is a complex scenario. This research is delimited on the Construction phase, more specifically about the craft workforce on-site performance. This work aims to study craft workforce productivity performance. Also, it is a target to collect data employing electronic devices for body acceleration assessment. The components of the tasks related to products and equipment are not part of this work, as well as other electronic methods of monitoring (e.g. filming).

1.5 OBJECTIVES

The main target is to design a framework to face the CI low productivity primary concern. Into the Construction 4.0 scenario, this research innovation core is the electronic performance monitoring applying wearables sensing technologies to transponder the manual data collection barrier. The central goal is to provide CI with a craft-workforce-centred dimension. The research set an agile assessment method focus on electronic productivity performance monitoring. The focus is to fill the gap on modelling and measuring craft workforce on-site activities. The research aims to deliver tasks, process mapping and information management, all aligning with GDPR compliance.

Finally, the thesis main aim is to develop a framework to measure craft workforce productivity. Being the objectives:

- Conceptualise an approach to assess and modelling craft workforce productivity;
- Provide in-depth knowledge to enable GDPR compliance;
- Conceptualise the EPM data flow, connecting system/methodologies;
- Testing the EPM application and validation of the proposed framework.

It is intended to obtain answers to a set of questions related to the CI and innovative data/information management based on EPM, being:

1. What are the productivity concept, and how to assess it in the CI?
2. What are the existing methods to measure and manage work systems?
3. What are the most appropriate dimensions/levels to evaluate and improve productivity?
4. What are the legal and ethical aspects regarding electronic data collection from construction workers? What are the impressions about EPM at managers' levels?
5. How to share on-site' information with stakeholders by different systems?
6. What are the key performance indicators in construction project management?
7. What is the state-of-the-art on electronic performance monitoring?

The proposed framework has direct implications upon the characteristics of the works to be developed, the site conditions, and the type of organisation and willingness of the workers. These assume a crucial role in terms of future headings of the research and, at the same time, constitute an opportunity to raise the bar of the industry image regarding the craft workforce.

The contributions to the body of knowledge are substantiated on the framework created with the ability to model and assess craft workforce performance. This approach is meant to serve as a base point for different stakeholders focusing on skills, efficiency, mechanisation, and productivity improvements.

1.6 METHOD

According to Crotty (1998: p.3), the essential elements of a research process are [48]:

- Epistemology: "The theory of knowledge embedded in the theoretical perspective and thereby in the methodology" [48].
- Theoretical Perspective: "The philosophical stance informing the methodology and thus providing a context for the process and grounding its logic and criteria" [48].
- Methodology: "The strategy, plan of action, process or design lying behind the choice and use of particular methods and linking the choice and use of methods to the desired outcomes" [48].
- Methods: "The techniques or procedures used to gather and analyze data related to some research question or hypothesis" [48].

As stated before, this work "mix and match" methods to better achieve the particularities of this construction management research [3–5]. Based on Mukherjee et al. (2002: p.668), this research type was set as "**Type 3: Research is undertaken on an exploratory basis, conducted in real-time and with uncertain outcomes.** This perhaps exemplifies a significant amount of academic research, where the research parameters at the beginning are fairly flexible and the nature of the end products are also uncertain." [1]. Although much has been studied in the field of construction productivity and there is already some practical research in the field of EPM, little is focused on the craft workforce, and practically nothing focuses on on-site modelling activities. Pragmatism research philosophy [49] is the concept that fits this work. Taking this research approach into account, the following conditions are established, based on Al-Ababneh (2020: p. 82-83):

- Ontology: external and multiple views chosen to enable best and to achieve the objectives [49];
- Epistemology: "Both observable phenomena and subjective meanings can provide acceptable knowledge. Focus on practical applied research, integrating different perspectives to help interpret the data" [49].
- Axiology Data: "Values play a large role in interpreting results, adopting both objective and subjective points of view." [49].
- Data Collection Techniques: "Mixed or multiple method designs, quantitative and qualitative." [49].

Finally, the thesis research approach is based on five stages (Figure 1.2). Firstly an extensive literature review was conducted on many aspects directly and indirectly connected to the research. Based on that background plus the author's knowledge and that acquired from the stakeholders (e.g. supervisors, professors, colleagues, potential clients), innovative proposals were made. In order to have proposals' validation/improvements, specific surveys/interviews were conducted. Further, laboratory and on-site testing were applied proofing part of the concepts and frameworks. Simultaneously, academic papers were submitted/published/presented in journals and congress to achieve peer review proofing. Meanwhile, classes and courses were delivered in the academic and professional fields.

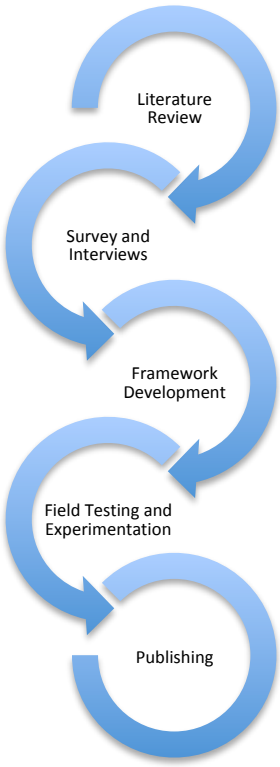


Figure 1.2 – Thesis research approach.

Forward in the next subsections, these interactive flows are detailed.

1.6.1 LITERATURE REVIEW

The research strategy based included searching in the top electronic databases in the field of construction, management and law which provided easy access to the following databases found in Index: Academic Search Ultimate, Current Contents, Web of Science, SCOPUS, INSPEC, and ScienceDirect. It also took place on E-journals provided by Cambridge University Press, Emerald Full text, Taylor and Francis, Oxford Journals, Scientific Electronic Library Online, Springer Link, ICE Virtual Library, and ASCE Library. For the search strategy, several keywords and combinations were considered based on the scope and focusing on the construction workforce. At the beginning of the search, every combination of the keywords was inserted in the electronic databases, with no study type, language or date limitation. Subsequently, limitations by date, type, source, language, and then the topic were introduced. The search strategy's final step was the search within the references of the collected articles to seek any relevant studies. Exclusion criteria were certain types of documents such as books reviews, papers with no access and off-topic.

Also, reports were collected from international management consultancies. Besides research books (mainly related to work management) and laws, regulatory norms were added to the review. Beyond, different pieces of information from reliable sources on the Internet.

Figure 1.3 presents the characteristics of the bibliography present in this research. Approximately 63% of the referenced documents have been published in the past five years. Where approximately 75% of these references are articles published in academic journals. With highlights to the Journal Automation in Construction with 22% of the total and the Journal of Construction Engineering and Management with 11% of documents out of a total of 298.

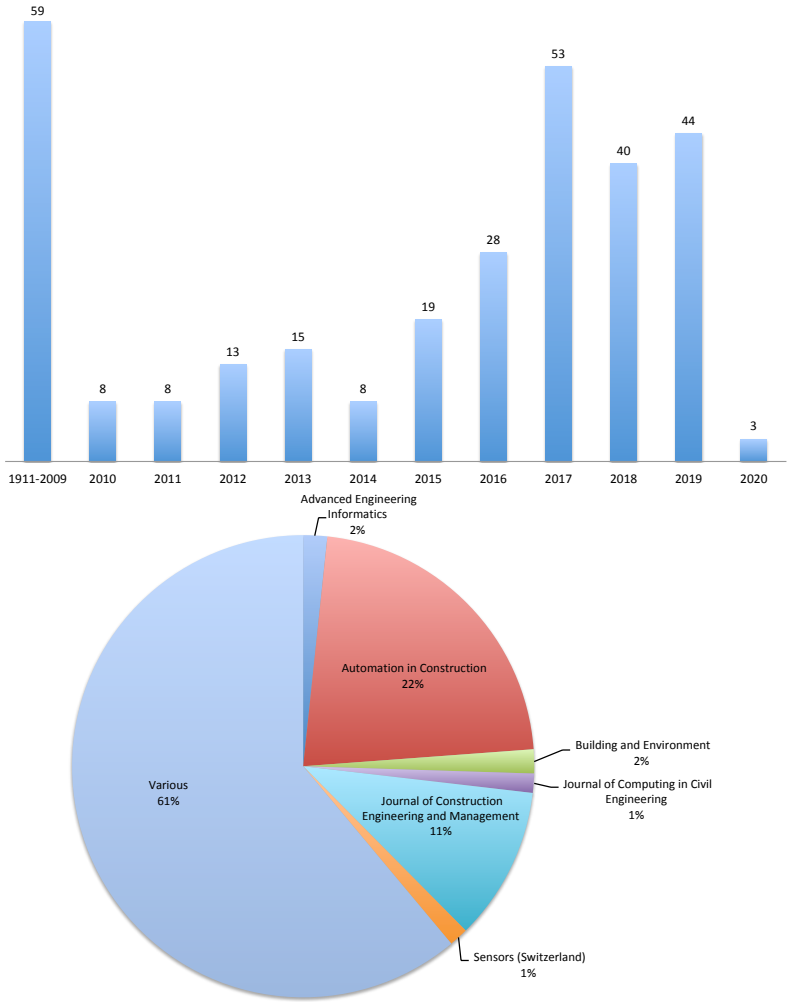


Figure 1.3 – Bibliography characteristics.

1.6.2 SURVEY AND INTERVIEWS

A survey containing twenty-five questions was proposed for collecting engineering's (workers and students) awareness about EPM at the workplace. Experts semi-structured interviews from three different countries were used to capture the conceptualizations and challenges regarding Worker 4.0 in the construction industry. Finally, an on-site experiment dressed up eight craft workers on duty with wearable devices and collected their impressions about EPM, interviewing then during the process. Figure 1.4 illustrates the integrated method applied to different stakeholders.

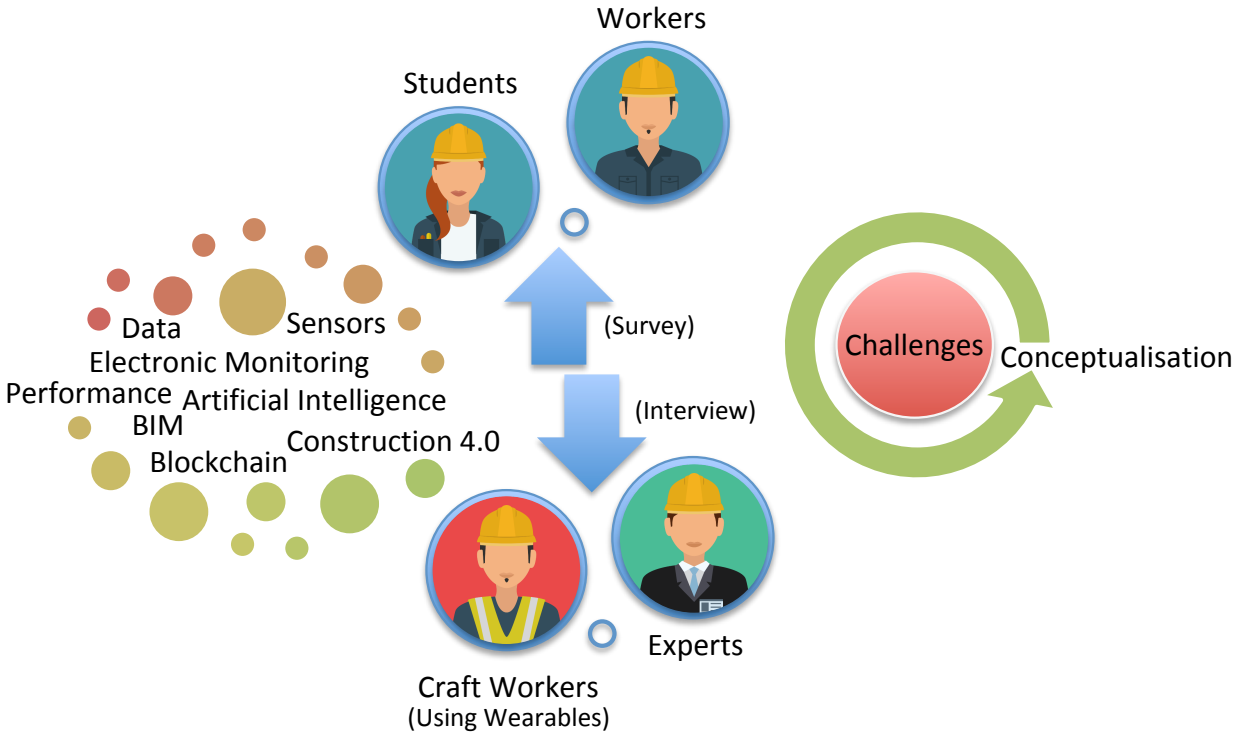


Figure 1.4 – CI 4.0: What do people think?

1.6.2.1 Survey for evaluating the people's concern/acceptance to EPM at work

A survey to collect the people impressions about electronic performance monitoring at work was developed. It was implemented in electronic format through the Google Forms platform, and it is presented in Chapter 3. It was sent electronically (e-mail and social networks) to students and workers with a higher education level. With this, the population sampled is predominantly of engineers, in fact, having as an everyday characteristic developing activity in office and management. This audience is sampled because they will be responsible for implementing EPM.

1.6.2.2 Experts' interview to validation/improvements of the Information Management 4.0 framework

Experts' interviews are used for validation/improvements of the information management framework presented in Chapter 4. Qualitative research is inductive, heterogeneous [50] and interpretive [51]. Semi-structured interviews are a form of qualitative research used to gather subjective data to form analysis and further understanding [52].

In this research scheme, the interviews were used to improve the framework by (dis)confirming the links in the processes framework and finding any gaps using the interviewees' intuition and experience. Opportunity and convenience sampling was used to select participants to gauge a broad perspective on the impact of using technology-driven data for performance monitoring and

enhancement. The participants had experience and practical knowledge in law, construction practice (management, culture etc.) and IT management (Information Technology).

The semi-structured interviews' approach was centred on the framework developed from the author's experience and intuition. The interviews opened by explaining the purpose of the framework and asking open questions about their perception regarding the possibility of using Electronic Performance Monitoring. These questions surrounded the following:

- Benefits and challenges of using EPM;
- Ways the data could be used to improve productivity, safety, quality etc.;
- Ways the data can be utilised in contractual agreements supported by blockchain;
- Way the use of the technology can be applied;
- Employee reaction to EPM;
- Impact and challenges to the employer;
- Views of using EPM and Artificial Intelligence (AI) in the construction industry;
- Effect of GDPR on the use of EPM and AI based decision making;
- Current legislation on the use of EPM and AI use;
- Way ethical and moral challenges can be minimised;
- Possible influence of algorithm bias on the framework;
- View of the framework, what gaps there are or what can be improved.

The most important findings from the expert semi structured interviews are presented in Chapter 4.

1.6.2.3 Craft workers' interview to evaluate EPM concerns/acceptance

Interviews with craft workers were conducted during the on-site testing to evaluate EPM concerns/acceptance. The interviews opened by explaining the purpose of using wearables sensing technology and asking open questions about their perception regarding the possibility of Electronic Performance Monitoring. These questions surrounded the following:

- The comfort/discomfort of using the wearables devices on the wrists and legs;
- The prospect of being monitored by academic purposes and future similar monitoring by the employer;
- The data ownership;
- The benefits/threats of using this type of monitoring technologies and the mechanization of work.

The most important findings from the interviews are presented in Chapter 7.

1.6.3 Framework Development

The core approach is based on hardware and software, see Figure 1.5. The physical elements (hardware) are associated with the workers themselves when performing their work routines using the wearables devices. The hardware is also the essential physical infrastructure of equipment to transmit, store, and process data. Associated with the devices and equipment are the native systems (software) for their operation. Finally, different systems (software) are needed to store and process data such as operating systems and databases. Throughout implementing the devices, their use, data collection and processing, various actors/knowledge are required.

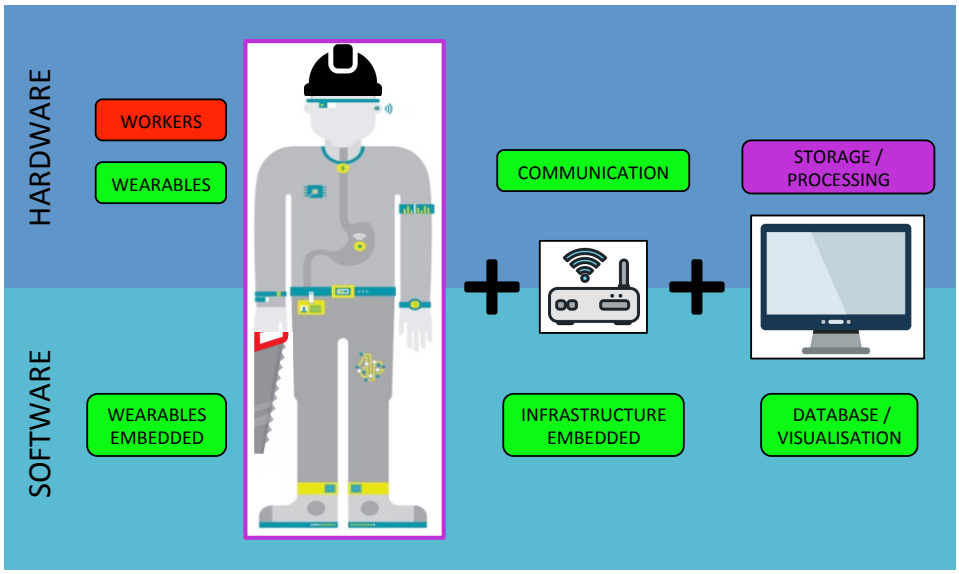


Figure 1.5 – Hardware and Software based.

Based on the literature review and past works developed by the author, a series of actions (e.g. frameworks, processes and, flows) were improved and developed:

1. Productivity assessment under different levels perspective (8 levels);
2. Worker 4.0 Processes for Motion Productivity (9 processes);
3. Worker 4.0 Flow to boost Productivity (Efficiency and Mechanization);
4. Worker 4.0 Mapping chart (Two-hand methodology);
5. GDPR Agreements (18 packages);
6. EPM-KPIs (13 key performance indicators);
7. Management 4.0 (EPM+BIM+AI+BLOCKCHAIN).

1.6.4 Field Testing and Experimentation

Workers' activities classification is one of the thesis focus. Based on that, experiments focused on using only the workers' body acceleration and observing their actions. However, it is based on the acceleration mainly of the upper and lower limbs that a micromotion analysis is possible. To run the feasibility of the frameworks presents on this thesis, limited verification was performed based on wearables to collect the acceleration (two wrists and one leg) and machine-learning plus multivariate statistical analysis for post-processing. Ten construction activities simulated an experiment in laboratory facilities covering four over nine processes of the proposed motion productivity framework.

In addition, data were collected on-site (through work sampling methodology) to measure and model two production processes typical of civil construction. Also, craft workers will dress up wearable electronic devices during the experiment and will be interviewed to understand their reactions to EPM. The method of both experiments will be presented in Chapter 7. Where the activities are:

- Water supply system (to consumers' taps);
- Masonry (residential building with expanded clay blocks);
- Masonry (commercial building with expanded clay blocks and concrete blocks).

1.6.5 PUBLISHING

It sought to publish articles in academic journals and presentations at congresses, classes, and courses to search for the consolidation and improvement of the innovative proposals present in this thesis. The dissemination of ideas and the contribution of audiences and per reviewers was a fundamental part in forming the concepts presented at the time. Nevertheless, working with other authors added knowledge and allowed the full development of the proposed concepts. Following, the list of publishing, presentations and academic works:

Papers published on academic journals

Calvetti, Diego, Miguel Chichorro Gonçalves, Fabrício Peter Vahl, Pedro; Meda, and Hipólito José Campos de Sousa. 2021. "Labour Productivity as a Means for Assessing Environmental Impact in the Construction Industry." *Environmental Engineering and Management Journal*. 20 (5).

Sanhudo, L., Calvetti, D., Martins, J. P., Ramos, N. M. M., Mêda, P., Gonçalves, M. C., & Sousa, H. 2021. Activity classification using accelerometers and machine learning for complex construction worker activities. *Journal of Building Engineering*, 35. https://doi.org/10.1016/j.jobe.2020.102001

Calvetti, Diego, Pedro Mêda, Miguel Chichorro Gonçalves, and Hipólito Sousa. 2020. "Worker 4.0: The Future of Sensored Construction Sites." *Buildings* 10 (169): 1–23. https://doi.org/10.3390/buildings10100169. (Special issue: Construction 4.0)

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Calvetti, Diego. 2018. "Multivariate Statistical Analysis Approach to Cluster Construction Workers Based on Labor Productivity Performance." *U.Porto Journal of Engineering* 4 (2): 16–33. https://doi.org/10.24840/2183-6493_004.002_0002.

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Sidani, Adeeb Ziad, J. Duarte, Fábio Matoseiro Dinis, L. Sanhudo, Diego Calvetti, João Poças Martins, and Alfredo Soeiro. 2018. "The Impact of BIM-Based Virtual and Augmented Reality Interfaces on Health and Safety in Construction Projects: Protocol for a Systematic Review."

International Journal of Occupational and Environmental Safety 2 (1): 67–74. https://doi.org/10.24840/2184-0954_002.001_0008.

Papers presented on congresses

Magalhães, Pedro Nuno Mêda, Hipólito José Campos de Sousa, Miguel Chichorro Gonçalves, Diego Calvetti, Fernando Camargo, and Paulo Dias. 2020. "People, Process, Technology in Construction 4.0 - Balancing Knowledge, Distrust and Motivations." In *18th International Conference on Computing in Civil and Building Engineering / 37th International CIB W78 Conference*.

Calvetti, Diego, Miguel Chichorro Gonçalves, Pedro Nuno Mêda Magalhães, and Hipólito José Campos de Sousa. 2019. "Sensing Technologies Embedding Construction Workers Outcomes / Key Performance Indicators." In *In Proceedings of the 36th CIB W78 2019 Conference: Advances in ICT in Design, Construction and Management in Architecture, Engineering, Construction and Operations (AECO)*, edited by Bimal Kumar, Farzad Rahimian, David Greenwood, and Timo Hartmann, 890–900. Newcastle, UK: ISBN (Print) 9781861354877, ISBN (eBook) 9781861354860.

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Thesis co-supervision

"Avaliação do impacto de aspetos de forma dos elementos na produtividade do assentamento de alvenarias.". Student: João Alberto Dantas Faria. *Mestrado em Engenharia Civil — Especialização em Construções.* Supervisor: Professor Ph.D. Hipólito José Campos de Sousa. (2020).

1.7 ORGANIZATION

Figure 1.6 shows the main flow of this document. The thesis was developed to respond to the main issues stated in the motivation section above. The thesis Chapters and contents are:

- Chapter 1: Introduction;
- Chapter 2: The concept and assessment of Productivity in the Construction Industry (CI);
- Chapter 3: GDPR compliance and People thoughts about EPM;
- Chapter 4: Information Management 4.0;
- Chapter 5: Sensored Construction Sites;
- Chapter 6: Craft Workforce Motion Productivity;
- Chapter 7: Testing EPM and Validation of the Proposed Framework;
- Chapter 8: Conclusion.

Productivity in the construction industry is a complex issue. The study developed in this thesis seeks different approaches and analyses to create a framework to assess craft workforce productivity. Chapter 1 introduces the work, presenting the problems and goals. Also, the thesis method was presented to show the interconnection of multiple methodologies to achieve the work objectives.

The thesis core state-of-the-art is concerns productivity and electronic performance monitoring. The background is mainly delivered in Chapter 2 (The concept and assessment of Productivity in the Construction Industry), Chapter 3 (GDPR compliance and People thoughts), Chapter 4 (Information Management 4.0), Chapter 5 (Electronic Performance Monitoring). Although the works deliver the pertinent background for contextualisation in all sections, Chapter 6 brings concepts of work systems and motion studies to sustain the proposed innovation for Craft Workforce Motion Productivity.

Chapter 3 raises light on people's concerns about electronic monitoring. The work presents an investigation about European regulations and delivers critical information for GDPR compliance. Also, a conducted survey was analysed to understand better what people think and measure the level of acceptance of electronic monitoring at the workplace. Focusing on craft workers' data interaction, Chapter 4 frameworks KPIs and systems flows to achieve CI useful information. Based on the background, the key performance indicators are interconnected to the craft workers dimension. Experts' opinions validated the system's flow, highlighting the main opportunities/barriers regards data collection, storage, and processing.

Most important, Chapter 7 presents a series of practical applications to test and validate the proposed framework. Construction tasks circuit activities were designed in a university laboratory to test and postulate the electronic collection (wearable devices) and data processing (machine-learning). Furthermore, on-site experiments sampling construction activities and fulfil the processes modelling proposed on the Worker 4.0 Motion Productivity method. Finally, craft workers are introduced to electronic performance monitoring by wearing devices and confronted with this new 4.0 world when they delivered feedback about, for example, data ownership, wearables dressing comfort/discomfort, and the mechanisation of the work.

Chapter 8 brings work conclusions. Moreover, looking ahead, products/outcomes from this work are presented, as well, a vision of future developments is highlighted. The primary outcome is to provide tools to empower the craft workforce to have ownership of their own data. Most important than the brand "Worker 4.0" is the slogan that comes together: "my work, my data.".

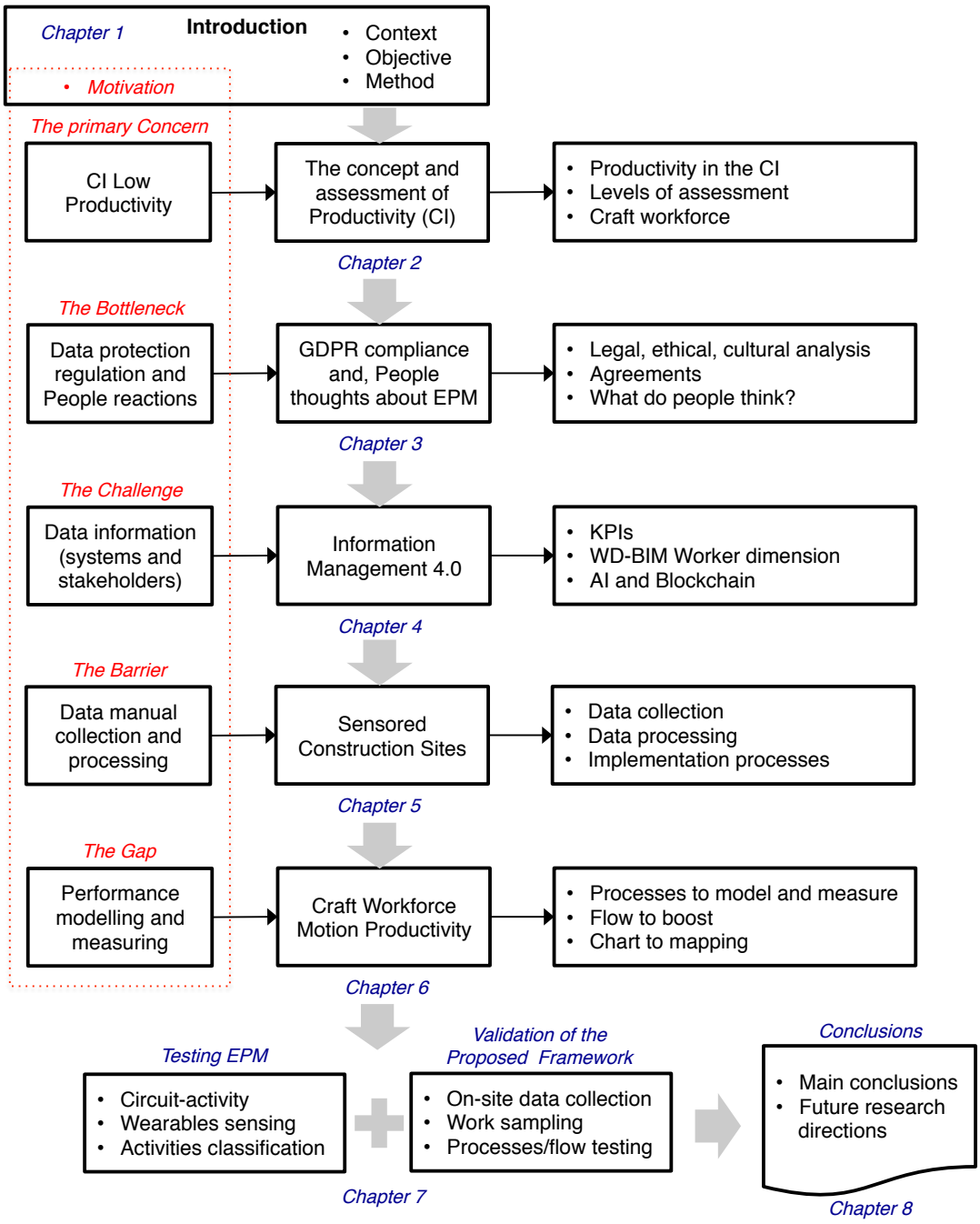


Figure 1.6 – Thesis structure.

2
THE CONCEPT AND ASSESSMENT OF PRODUCTIVITY IN THE CONSTRUCTION INDUSTRY (CI)

2.1 INTRODUCTION

In this chapter, productivity at CI is assessed. It seeks to understand the challenges and evaluate the existing models for measuring and evaluating productivity in the sector. However, the firsts research questions are sought to be answered:

1. What are the productivity concept, and how to assess it in the CI?
2. What are the existing methods to measure and manage work systems?
3. What are the most appropriate dimensions/levels to evaluate and improve productivity?

2.2 PRODUCTIVITY IN THE CONSTRUCTION INDUSTRY

2.2.1 PRODUCTIVITY CONTEXT

The measurement and evaluation of productivity in the CI can depend on regional issues and cultural aspects as in other economic activities. Distortions in the productivity assessment are introduced by many parameters such as: the size of the economy and the companies [11,12]; the government regulation [13,14]; the level of process automation [15]; society's preferences in terms of requirements [13,16]. The type of materials and equipment available where construction takes place most often guides the solutions and subsequently, the project's scope. Another relevant aspect is the weather conditions, which significantly affect construction sites around the world [53]. All these aspects have some influence on the work environment and the work processes during the construction phase.

It can be stated that in periods of economic crisis, there are disinvestments in construction, which can be added to a depreciation of the local currency [11,54–56]. USA firms have higher productivity rates than European and Asian companies [11]. Countries with developing economies have a more significant housing and infrastructure deficit compared to developed economies. In growing countries, the human resources of construction are cheaper and, on the other hand, less qualified. Developed countries have a higher automation index in their processes, and this can increase productivity. Chancellor and Lu (2016) pointed out that China's construction market appears to be more efficient in large-scale operation than technically efficient [57]. Multinational construction companies suffer from host countries' effects and need to adapt to local particularities [58].

Sveikauskas et al. (2016) studied the productivity growth of single-family homes, multifamily housing, highways and industrial construction [14]. Moreover, it was found that the immigrant labour force works without documentation [14]. As a result, it does not explain the statistics, which imply a distortion in productivity indices [14]. The U.S. construction workforce in 2009 was comprised of 22.5% of Hispanic workers [59]. Besides, Dai and Goodrum (2011) emphasize that the first spoken language impacts productivity issues; firstly, there are communication barriers with supervision [59]. Also, Spanish-speaking workers have insufficient training in safety, health, and task skills [59].

In the USA, off-site tasks such as curtain walling, structural steel and precast concrete manufacturing have increased productivity at a higher level than on-site tasks due to automation of the production methods [15]. Unlike the manufacturing sector, the USA CI is highly fragmented due to many self-employed workers [12]. The fragmentation is somewhat global in the CI, despite the different reasons for this to happen. Heavy construction companies mainly develop projects in the industries, infrastructure and non-residential areas, dealing with the governments most of the time [11]. On the other hand, residential construction companies business generally deals with direct consumers in housing construction [11]. The construction sector is heterogeneous and, the field of activity and size of firms influence productivity efficiency [12]. Therefore, it is vital to identify the region (Country/City) of the analysis correctly.

2.2.2 LABOUR PRODUCTIVITY IMPACT FACTORS

Several impact factors affect construction labour productivity. Due to the complexity of the modelling and the determination of each impact factor's quantitative influence on the production of labour productivity, many approaches are used. Techniques of fuzzy inference systems (FISs) are prone to model construction labour productivity [60,61]. Several factors positively affect workforce productivity, such as workers' ability, motivation and project management efficiency. Other factors have a negative influence, among then, inappropriate area to perform the work, fatigue and no familiarity with new techniques of execution [62]. Nasirzadeh and Nojedehi (2013) introduce a system dynamics to model this process of positive and negative labour productivity interaction [62]. The artificial neural network (ANN) technique approach is applied to quantify multiple factors' effects on productivity [63–66].

Often, academic studies use a Relative Importance Index (RII) approach to rank the impact factors collected in surveys. Horner et at. (1989) set a ranking containing 13 factors that influence labour productivity in the United Kingdom [67]. Based on that starting point, many authors have investigated local impact factors. It can be seen that many unproductive impact factors are connected to regional problems such as incentive/payment, political issues, and harsh weather conditions [68,69,78–81,70–77]. Besides, factors as lack of products (materials and elements) and design specifications most often are significant productivity issues. Craft-workforce's performance and on-site tasks processes also achieved the top productivity issues in construction sites worldwide. Following it is highlighted the impact factors most connected to workforce/tools/supervision on at least the top 13 impact factors identified in academic works worldwide from 1989 until 2020.

British constructors (1989), factors identified [67]:

1. **Skill of labour;**
2. Buildability;
3. **Quality of supervision;**
4. **Method of working;**
5. Incentive scheme;
6. Site layout;
7. Complexity of construction information;
8. **Crew size and composition;**
9. **Length of working day;**
10. **Availability of power tools;**
11. **Absenteeism;**
12. **Total number of operatives on-site;**

13. Proportion of work subcontracted.

Singapore constructors (1995), factors identified [68]:

1. Difficulty in recruitment supervisors;
2. **Difficulty in recruiting workers;**
3. **High rate of labour turnover;**
4. **Absenteeism;**
5. **Communication problems with foreign workers;**
6. Inclement weather that requires work stoppage for one day or more;
7. Health issues (e.g. mosquito breeding);
8. Materials shortages;
9. **Alcoholism and similar problems among workforce;**
10. Disruption of power/water supplies;
11. Labour disruptions (e.g. manpower shortages, strikes);
12. Delays in materials deliveries to site;
13. Work stoppages because of insolvency of subcontractors/suppliers.

Iran constructors (1996), factors identified [69]:

1. Lack of materials;
2. Weather and site condition;
3. Equipment breakdown;
4. Drawing/spec./change order;
5. **Lack of proper tools and equipment;**
6. Inspection delay;
7. **Absenteeism;**
8. Safety (accidents);
9. **Improper plan of work;**
10. **Rework;**
11. **Changing crew size/ turnover;**
12. Interference at work;
13. Poor communication and MIS;

Indonesian constructors (1997), factors identified [70]:

1. Lack of material;
2. **Lack of tools;**
3. **Equipment breakdown;**
4. **Rework;**
5. **Changing of workers;**
6. Interference;
7. **Absenteeism;**
8. Supervision delays;
9. **Changing of foremen;**
10. **Too much work;**
11. **Over crowded.**

Malaysian constructors (2005), factors identified [71]:

1. Material shortage at project site;
2. Non-payment (financial problem) to suppliers causing the stoppage of material delivery;
3. Change order by consultants causing project delay;

4. Late issuance of construction drawing by consultants;
5. Incapability of contractor's site management to organise site activities;
6. Late issuance of progress payment by client to contractor;
7. Late supply of materials in the market;
8. Lack of foreign and local workers in the market;
9. Coordination problem with subcontractor;
10. Equipment shortage;
11. Lack of coordination among consultants;
12. Coordination problem with supplier;
13. Rework.

Uganda constructors (2007), factors identified [72]:

1. Incompetent supervisors;
2. Lack of skills of the workers (e.g. inexperienced, poorly trained);
3. Rework;
4. Lack of tools/equipment;
5. Poor construction method;
6. Poor communication;
7. Stoppages because of work being rejected by consultants;
8. Political insecurity;
9. Tools/equipment breakdown;
10. Harsh weather conditions;
11. Stoppages because of insolvency;
12. Poor recruitment and changing of foremen;
13. Stoppages because of disputes with owners/consultants;

Gaza Strip constructors (2007), factors identified [73]:

1. Material shortage;
2. Lack of labour experience;
3. Lack of labour surveillance;
4. Misunderstanding between labour and superintendents;
5. Drawings and specifications alteration during execution;
6. Payment delay;
7. Labour disloyalty;
8. Inspection delay;
9. Working 7 days per week without taking a holiday;
10. Tool and equipment shortages;
11. Rework;
12. Misuse of time schedule;
13. Accidents.

New Zealand constructors (2011), factors identified [74]:

1. Rework;
2. Level of skill and experience of the workforce;
3. Adequacy of method of construction;
4. Buildability issues;
5. Inadequate coordination, supervision, performance monitoring and control;
6. Statutory compliance (Resource Management Act);
7. Unforeseen events (Ground conditions necessitating revisions);

8. Other external forces (economical, political, etc.).
9. Clients' overt influence on the construction process;
10. Relationship management/ degree of harmony, trust and cooperation;
11. Adequacy of planning and risk management process;
12. Project organisational culture;
13. Project management style.

Kuwait constructors (2012), factors identified [75]:

1. Clarity of technical specifications;
2. Extent of variation/change orders during execution;
3. Coordination level among various design disciplines;
4. **Lack of labour supervision;**
5. Proportion of work subcontracted;
6. Design complexity level;
7. Lack of incentive scheme;
8. **Lack of construction managers' leadership;**
9. Stringent inspection by the engineer;
10. Delay in responding to RFI;
11. High/low temperature;
12. High humidity;
13. Compatibility and consistency among.

Palestine constructors (2013), factors identified [76]:

1. Political situation;
2. **Equipment's shortages;**
3. Old and inefficient equipment;
4. **Lack of labour experience;**
5. **Poor site management;**
6. Poor communication and coordination between construction parties;
7. Payments delay by the owner;
8. Low wages;
9. **Rework;**
10. Misuse of time schedule;
11. **Lack of training sessions for labours;**
12. Lack of financial motivation system;
13. Frequent change orders.

Egypt constructors (2014), factors identified [77]:

1. **Labour experience and skills;**
2. Incentive programs;
3. **Availability of the material and ease of handling;**
4. Leadership and competency of construction management;
5. **Competency of labour supervision;**
6. **Construction technology (construction method and material);**
7. Labour operating system (daily wage, lump sum);
8. **Planning, work flow, and site congestion;**
9. Constructability (integrated design and construction);
10. Clarity of instructions and information exchange;
11. Surrounding events (revolutions);

12. Weather effect (temperature, humidity);
13. Laborer age.

Indian constructors (2015), factors identified [78]:

1. Unavailability of material on time at workplace;
2. Delayed material delivery by the supplier;
3. Strikes called by political parties or hartals;
4. Frequent revisions of drawing/design resulting in additional work/rework;
5. Unavailability of drawings on time at the worksite;
6. **Craftsmen absenteeism;**
7. Improper project coordination;
8. Harsh weather conditions;
9. **Craftsmen turnover;**
10. Poor project planning and scheduling;
11. Errors in the drawings;
12. Equipment necessary to do the job not available on time;
13. **Lack of experience of craftsmen.**

Jordan constructors (2016), factors identified [79]:

1. Poor planning and scheduling;
2. Material shortage at project site;
3. Equipment shortage;
4. **Lack of skilled labour;**
5. **Poor site management;**
6. **Rework;**
7. Old and inefficient equipment;
8. **Lack of supervisors experience;**
9. Payment delay to the suppliers;
10. Slow response of consultant's staff attending inspection of work;
11. Lack of financial motivation system;
12. Financial conditions of the contractor;
13. Work overtime Design.

Vietnamese constructors (2018), factors identified [82]:

1. **Experiences of workers;**
2. **Labour discipline;**
3. Types of salary payment;
4. Quality of building materials;
5. **Ability to organize production;**
6. **Quality of working tools;**
7. **Construction supervision;**
8. Safety equipment;
9. **Physical ability;**
10. Height of working place;
11. Working in hazardous areas;
12. Staff support;
13. Reward mechanism.

Libya constructors (2020), factors identified [80]

1. **Lack of labour supervision;**
2. **Experience and skill of labour;**
3. **Construction technology;**
4. Coordination among design disciplines;
5. Errors in design drawings;
6. Delay in responding to requests for information;
7. **Rework;**
8. Lack of incentive scheme;
9. Working overtime;
10. **Construction manager's lack of leadership;**
11. Payment delay;
12. Unavailability of materials;
13. Inspection delay by the engineer.

As the studies detailed above indicate, the workforce is perceived by builders as a factor of great relevance in terms of productivity in the global construction industry. This analysis, once again reinforces the central role of the worker in the CI production process.

2.2.3 PRODUCTIVITY LOW GROWTH A GLOBAL CHALLENGE

Automation effectiveness is much more significant in other industries particularly in manufacturing [7]. The Construction Industry productivity is still been manly dominanted by the labour force work. Numerous failures account for the CI low performance, as Farmer (2016) pointed out ten main factors of CI failure and poor performance in the UK such as [7]:

- Low Productivity;
- Low Predictability;
- Structural Fragmentation;
- Leadership Fragmentation;
- Low Margins, Adversarial Pricing Models & Financial Fragility;
- A Dysfunctional Training Funding & Delivery Model;
- Workforce Size & Demographics;
- Lack of Collaboration & Improvement Culture;
- Lack of R&D & Investment in Innovation Poor;
- Poor Industry Image. [7]

Low productivity at CI is a global phenomenon. For example, leading developed countries in technology such as Japan, France and the USA experienced shrinkage in CI productivity from 1995 to 2017 [6]. In other developed countries like Canada, Germany, and the United Kingdom, productivity growth in construction was recorded below other industries' performance [6]. Some developing countries have low productivity, such as Brazil, as a reflection of economic and political instability and Saudi Arabia, which only used immigrant workers to increase production scale [6]. Good examples are found in countries such as China, India and Turkey, which have experienced a more significant acceleration in productivity in the construction sector [6]. Finally, CI productivity in Australia, Belgium, and the Netherlands have maintained positive growth over the years, and their characteristics may indicate a path towards global solutions [6].

Improve on-site execution is a bottleneck [6,7]. Many different stakeholders populate CI on-site, demanding numerous resources with many contractors and many subcontractors in the same enterprise [6,7]. There is no single solution that works for so many different contexts. It is necessary to create mechanisms and methods of analysis capable of measuring local performances and carrying out more effective actions [6,7].

2.2.4 PRODUCTIVITY MEASUREMENT IN THE CI

Measuring productivity in the CI is challenging given the industry's heterogeneous activities, as well as the extensive range of equipment, materials and human resources involved in the construction tasks. Therefore, to measure productivity adequately, it is necessary to go through the evaluation methods, metrics and quantitative parameters.

H. Randolph Thomas and Sakarcan Ahmet (1994) detailed a factor model for labour productivity based on the integration of three work elements. The "Work Method" is the way of converting technology into the form of tasks [83]. The "Work to be Done" are the specifications and requirements that guide the way how tasks are executed [83]. The "Work Environment" is the management and external factors that positively or negatively influence productivity [83]. Figure 2.1, presents develops and expands the "Work Environment" context of this model through the combination of other studies. The model is achieved by adding factors that affect construction labour productivity (e.g. Motivation of labour; Skill of labour; Physical fatigue; Shortage of experienced labour; High/low temperature; Extent of variation/change orders during execution; Accidents as a result of inadequate safety program; Site layout; Late arrival, early quits, and frequent unscheduled breaks) [75]. Labour unproductivity factors in construction projects (e.g. quality level; working out of sequence lack; deficiency in the financial source) [62] constitute the "Work Environment" additional final piece.

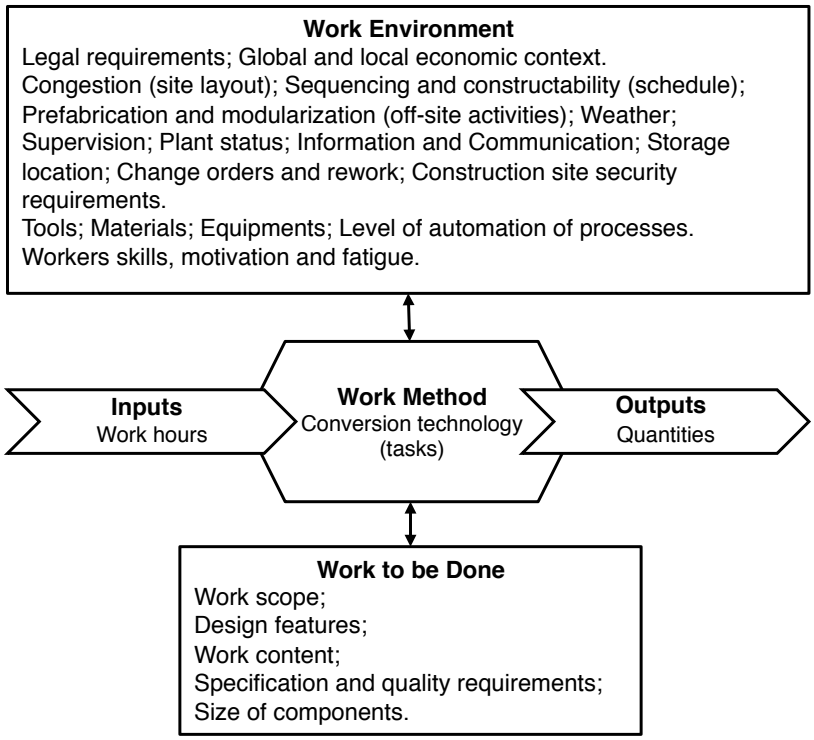


Figure 2.1 – Expanded factor model for labour productivity (adapted) [62,75,83].

Concepts as Benchmarks, KPIs and Balanced Scorecards are based on quantitative values. The construction workforce productivity measurement is mainly related to production and the correlation of inputs-outputs [11,84–87]. DEA's renowned methodology (Data Envelopment Analysis) is widely used to indicate baseline productivity based on quantitative values [55,57,88,89]. Baseline productivity can provide sector benchmarks at a given level, or the standard performance achieved at current operations [89]. Efficiency in daily work tasks is connected to workers' learning curve model in workaday operations [90].

Construction labour productivity can be affected by several impact factors. Due to the complexity of modelling, different approaches have been developed over time on the processes to find the quantitative influence of each impact factor on labour productivity production. Some examples are:

- the Relative Importance Index (RII) to rank surveys [75];
- the technique of fuzzy inference systems (FIS) to model productivity [60,61];
- the artificial neural network (ANN) approach to quantify the effects of multiple factors on productivity [63–66].

Labour modelling and measuring are more commonly applied in manufacturing working design than in the CI. The approach of modelling/measuring manual work systems sets the way for a comprehensive understanding of construction labour productivity. Studies based on work design and motion study (e.g. direct time study, work sampling and ergonomic/physical analyses) are able to assess all the three dimensions of the labour productivity [90–92].

CI projects follow a task/construction work vision. Methodologies such as project/schedule oriented by WBS (Work Breakdown Structures) frame the deliverables until work packages level [93]. Likewise, the Construction Industry Institute (CII) provides a more detailed design and construction execution through a system of Work Packaging & WorkFace Planning [94]. Forward, those work packages or tasks fulfil the schedule networks in the projects' process of planning, being usually simulated through CPM (Critical Path Method) or PERT (Project Evaluation and Review Technique) [93].

Simulation processes tools based on DES (discrete event simulation) have been applied in the construction field in order to assess and increase productivity. Examples of these tools include the (CYCLONE) Cyclic Operations Network [95], and the STROBOSCOPE (STate and ResOurce Based Simulation of COnstruction ProcEsses) [96]. Creating a process model on Stroboscope to connect video image and real situations foster a rapid productivity analysis of construction operations [97]. Workforce activities duration collected by smartphone (accelerometers and gyroscopes) were simulated on Stroboscope models in order to compare the data-driven model and static model [98,99].

2.2.5 PRODUCTIVITY ASSESSMENT UNDER DIFFERENT LEVELS PERSPECTIVE

2.2.5.1 Contries and Industries

At the Countries level, it is sought to compare the productivity of the construction industry in each nation in order to identify performances [6]. In this sense, generally, the economic dimension of productivity is the most relevant. The assessment indicators are related to historical data of the sector's gross domestic product (GDP) (output) and the volume of man-hours employed (input). How human resources are used in construction work in different countries and the production cycles of the CI (e.g.

post-war periods and economic crisis) create challenges for the productivity assessment over time [87].

Moreover, the difference in the exchange rates of different currencies generates distortions in international benchmarks and requires studies focused on deflators' development [87]. At the same time, other distortions may occur due to the actual numbers employed in the sector. For example, undocumented immigrants workers do not appear in Governments' control statistics [14], influencing the results.

The construction sector is highly heterogeneous, and the field of activity and size of companies influences productivity efficiency [12]. In order to make possible the comparison of different construction sectors at countries level, it is also vital for the applied deflators. Sveikauskas et al. (2016) detail four subsectors with renowned indexes: single-family housing; multiple-family housing; highways; and industrial construction [14]. At the Industrial level, the economic aspect is still the most relevant to evaluate and benchmark labour productivity in an output-input ratio approach [100].

Further, it is challenging to diagnose impact factors at industry levels accurately. This is related to variables such as management, labour, government, contracts, owner characteristics and financing [101]. Consequently, in order to have a deep understanding of the impact factors, it is necessary to carry out field analysis at Project and Task levels.

2.2.5.2 Projects and Tasks

It is precisely at Project level that it is possible to identify where and when the construction occurs. As a result, aspects of the "Work Environment" (e.g. site layout, schedule, weather, supervision, legal requirements, global and local economic context) become available, and it is possible to measure the impacts of those factors on the "Work Method" (tasks) and on the "Work to be Done" (e.g. specification and quality requirements, design features).

At the Tasks level, it is possible to measure the work methods' efficiency through the conversion technology of inputs delivery and outputs measurable. Within the CI, it is valuable to obtain the income from the tasks, i.e., the number of resources (human, products and equipment) required to obtain a constructed item (e.g. a square meter of masonry a cubic meter of concrete).

Park et al. (2005) emphasise that benchmarking and metrics at Task level require the measurement units' standardisation for inputs and outputs [85]. It is also at this level that the workflow is evaluated. Several models analyse the human, product and machinery resources within the productive cycles, mainly evaluating the sequence and interconnection of activities, the actions duration and standby states, and the amount of work performed.

2.2.5.3 Work and Motion Elements

Below the Task level, in the late 1800s and early 1900s, the study of work elements by Frederick W. Taylor and the study of workers' basic motions by Frank Gilbreth represented the beginning of the work's structure microanalysis [90,92,102].

The Basic Motion Elements are the instant movements (gestures that last less than a second) of the workers in service, and a Work Element is a performance, lasting six seconds or more, of multiple

basic grouped movements that represent a function in a task (e.g. scraping, hammering, cutting) [92]. At least one task can be delivered in a few seconds or a few minutes depending on the activity requirements [92].

From this it is possible to identify/define three lower/detailed levels/layers:

1. tasks;
2. work elements;
3. basic motion elements.

Different approaches to the definition of a hierarchical level of labour productivity boundaries have been developed. As example:

- Area, Activity and, task [103];
- Project, Division, Activity, Task, Elemental motion, Orthopaedics and, Cell [104];
- Project, Division, Activity, Basic task and, Elemental motion [105];
- Activity, Task, Action and, Movement [106].

Based on the levels above mentioned it was established the pyramidal structure for the assessment of CI productivity (Figure 2.2).

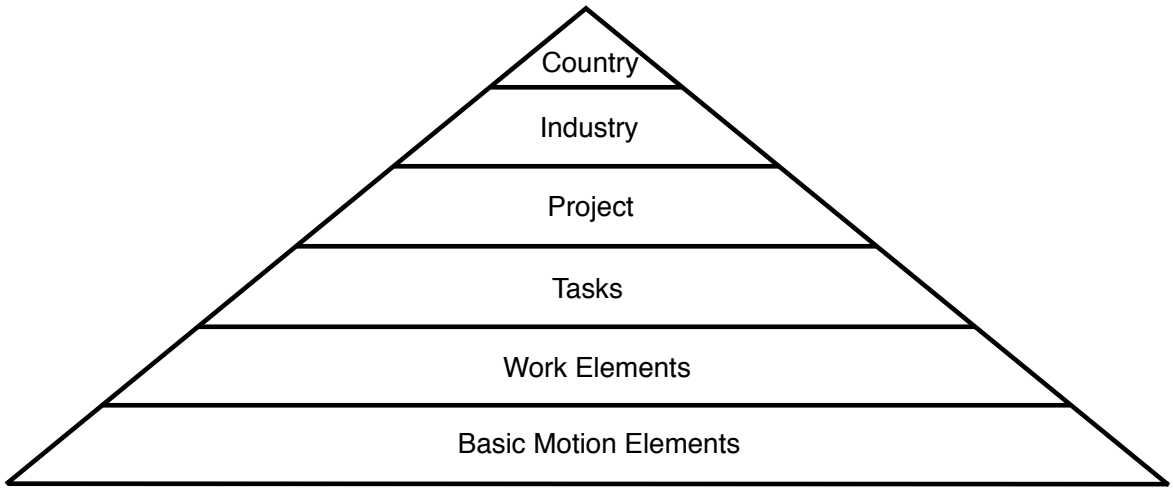


Figure 2.2 – Pyramidal structure for the assessment of productivity.

2.3 PROPOSAL FOR PRODUCTIVITY ASSESSMENT UNDER DIFFERENT LEVELS PERSPECTIVE

Likewise, in each of the six levels of the productivity assessment pyramid, the context must be taken into consideration for the evaluation methods and parameters to be applied, and the most appropriate data collection mechanisms. Yi and Chan (2014) indicate a macroscopic spectrum for the analysis of the CLP (Construction Labour Productivity) at a national level, considering a microscopic analysis at activity level [101].

As evidenced in Figure 2.2, this approach ranges from Country-level to Task level. El-Gohary et al. (2017) indicate that at Project level, there is a Micro Level (project management and administration) and at the Task level, there is a Micro/micro Level [64]. Finally, taking advantage of the opportunity for nanotechnology to monitor positions, movements, acceleration of materials, tools, equipment, and workers in on-site activities, this spectrum of analysis is completed with a "nanoscopic" dimension, allowing the assessment of work elements and basic motion elements. Consequently, Figure 2.3 presents the proposed pyramidal framework to measure CI productivity under different levels of perspective.

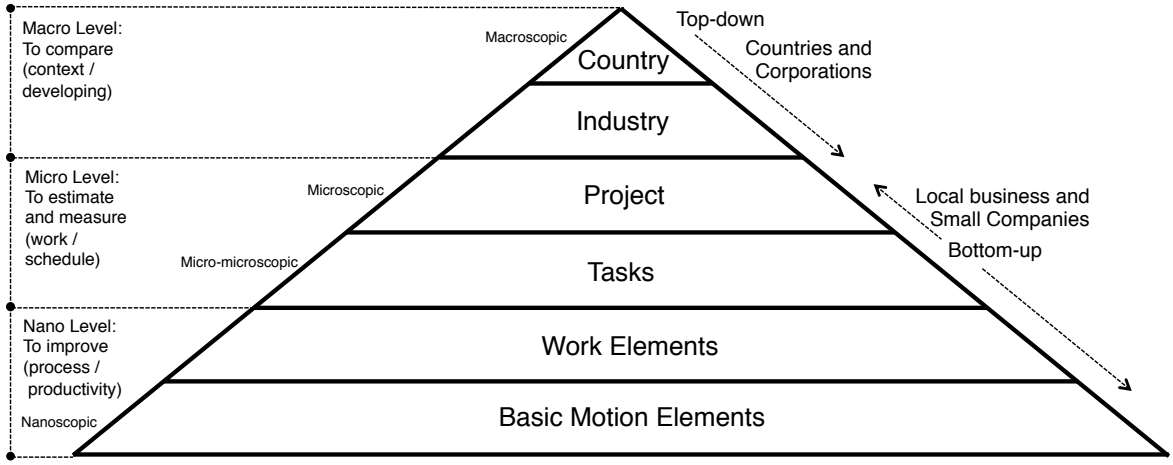


Figure 2.3 – The approach levels to measure productivity.

Within a Macro Level analysis, the countries are included, as well as the industry (sectors: construction, services, manufacturing or sub-sectors of the construction industry: residential, non-residential). The analysis of macroeconomic aspects is relevant at this level for the comparison/evaluation of countries and sectors' development status.

The primary tool to measure productivity is the ratio of inputs to outputs based on historical data from Governmental statistics and employment-related institutions. In this sense, as mentioned before, attention must be given to the CI context, where several factors should be considered. In this spectrum, it is possible to determine a benchmarking based, among other things, on the relation between the GDP and the man-hours employed, in order to perceive the main barriers that productivity growth faces.

Countries for benchmark and large corporations for decisions on transnational projects should take a top-down approach. On the other hand, smaller companies with local businesses, or even large construction companies locally positioned should take a bottom-up approach to improve processes and increase the level of competition. Either way, both approaches end their analysis at the centre of the pyramid, to diagnose the impact factors of productivity and to measure and develop on-site productivity metrics.

It is possible to determine, at the context and barriers level, a benchmarking based on the relation between the GDP and the man-hours employed and perceive the main barriers that worldwide productivity growth faces. Conducting, for a view of the productivity impact factors at each site, requires analysis at lower levels. When the input-output ratio is applied, the quantitative efficiency of

the applied conversion technology is measured. When measuring impact factors that cause unproductiveness and productivity, the influence of the work environment and the aspects of the work to be carried out in the development of tasks are detected. However, when assessing productivity by modelling work processes, such as the study of movement, time, and work design, the full picture is visualised, which means the work to be performed, the work method and the working environment.

Furthermore, overseeing the interaction between the factor model of labour productivity (Figure 2.1), the assessment and measurement methodologies (section 2.2.5), and the levels to approach the pyramidal structure in assessing productivity (Figure 2.3). It can be seen that the context and barriers to assessment productivity are at a Macro level, above others, just linked with the work environment and acting as restriction and impact factors. However, the input-output methodology is connected with all levels, also is an essential input of the others methodologies, and it is strictly linked with the work method. Finally, the impact factors identification methodology and the modelling process are connected to the Micro and Nano levels and linked whit all the factor model of labour productivity.

A view of productivity impact factors at each site requires an analysis at lower levels. Projects and tasks are already included in a Micro Level analysis, where more detail about the "Work Environment" and the "Work to be Done" requirements can be diagnosed. At Project level, aspects of the "Work Environment" connected to management can be perceived (e.g. sequencing and constructability; supervision; information and communication; change orders and rework; construction site security requirements; legal requirements; global and local economic context.), and also, aspects directly connected to the "Work to be Done" (e.g. specification and quality requirements; design features; work scope).

Furthermore, at the Task level, it is possible to observe aspects related to the "Work Environment" (e.g. weather; plant status; equipment; tools; materials; the level of processes automation; workers skills and motivation; storage location) and "Work to be Done" (e.g. size of components), in addition to measuring the efficiency of the "Work Methods", based on ratio input-output metrics of the tasks. At this level, the scope is developed, and task-based WBS is used to guide planning and production control measurements. Nevertheless, an evaluation of the impact factors on productivity and approaches to modelling the work processes are available at this Micro Level.

Finally, at the bottom of the pyramid is there the Nano Level of analysis. Basic Motion Elements and Work Elements are perceived, fostering a Nano assessment of the craft workforce productivity. It is through the physical and mental effort of direct labour that construction activities are performed. The physical and manual effort can be replaced or attenuated by using types of equipment, machines or power tools.

A built object gains shape during the manufacturing and construction phase [107] and through a succession of tasks involving construction products, equipment's (and construction aid) and human labour, namely craft workforce physical and mental effort. In this respect, some tasks can be developed only with human strength and technical skills or can be supported (efforts attenuated in some cases) with the use of hand tools (e.g. wrench, hacksaw, trowel) [92], portable power tools (e.g., drills, circular saw, routing tools) or other accessories. In other cases, the workforce can operate machines/equipment (e.g. crane, backhoe, walk-behind vibratory-plate compactors). In all these situations, construction products are involved as a construction resource that is transported, assembled or transformed and placed off-site to lead or be part of a construction element or system [45,108].

Within the current construction framework, even in activities with a high degree of mechanisation, operators' presence is still required [45]. In fact, craft workforce performance is the primary productive factor in the construction industry [45]. Few processes are based on automated systems [92]. However, within the current reality, even in activities with a high degree of mechanization, a human operator's intervention is still necessary. Human resource performance is the primary productive factor in the status quo of the CI. At EU-28 level, construction employs more than 50%, 56% to be more precise, of its labour force as "crafts and trade workers" [17]. In this sense, the analysis of the workers' location, movement, gestures, and even physiology (e.g. fatigue and degree of concentration), is highly relevant. Following the proposal at Nano Level, it is possible to perform detailed analyses capable of diagnosing the task processes and thus understanding processes technological conversion and inefficiencies diagnosis. Process improvement actions are essential tools to increase productivity.

It is essential to highlight that manual data collection by direct observations is an ancient practice. Nevertheless, it is time-consuming, costly, labour-intensive and highly prone to failures [24]. Framing this practice with privacy issues, it is also relevant to emphasise that manual data collection relies upon one person looking from close to others that are performing a task and taking notes from it. Furthermore, data post-evaluation models are more effective when the work process is routinely repeated [24]. In the case of CI, where projects have higher non-repeatable work processes, post-data evaluation techniques have limited gains [24].

2.4 CHAPTER CRITICAL REVIEW

The concept of productivity is broad. As seen in this chapter, the regional context and the immense boundary variables make CI productivity a complex problem. Among the various actors and productive processes within CI, it is understood that craft workers are the productive driving force. Therefore, the work is based on the study of productivity in the dimension of the craft workforce. Before moving on to an approach to implement EPM, it is necessary to check the feasibility of these approaches, aiming to assess GDPR compliance and seek to understand what the people who will do the management/execution of these projects think about EPM. However, in the next chapter, an in-depth assessment of the current regulation is carried out, and also, a survey is carried out with managers (and future managers) from the engineering areas.

3
GDPR COMPLIANCE AND, PEOPLE THOUGHTS ABOUT EPM

3.1 INTRODUCTION

The General Data Protection Regulation (GDPR) compliance is a primary concern in the employees/employers data exchange relationship. Yet, GDPR is a new regulation and concerning electronic monitoring of workers, and there are no case law records nor established agreements that, in practice, generate a gap. Finally, GDPR is both an enabler and a bottleneck for the implementation of sensored construction sites. As worksite-sensing monitoring is a new and complex scenario, it is necessary to broaden stakeholders' awareness to allow the test and execution of these kinds of projects. In this Chapter, a GDPR detailed analysis is made as well a survey is conducted to collect the managers-level impressions regarding EPM to respond to the following question:

4. What are the legal and ethical aspects regarding electronic data collection from construction workers? What are the impressions about EPM at managers' levels?

3.2 CONTEXT

The new European Union General Data Protection Regulation (GDPR) is a milestone in data privacy regulation [18,109–111]. The GDPR addresses the relationship between employers and employees, Recital 155 and Article 88, and issuance of the State Members auto-regulation through working collective-agreements [112]. The construction collective-agreement from Portugal does not specify any form of workers' performance monitoring [113]. Additionally, the Portuguese Work-Code in Article 18 (2) page 14 states that: "Processing of biometric data is only allowed if the data to be used is necessary, appropriate and proportionate to the objectives to be achieved." [114]. At the same time, the Portuguese specific law for "Data Protection" indicates the following regards biometric data: "Processing of workers' biometric data is considered legitimate for assiduity control and access to employer facilities, and should only ensure that representations of biometric data are used, and the process of unauthorised use is reversible." (Translation from law 58/2019 Art. 28 - 6, page 11) [115]. Consequently, addressing to Portuguese regulation, for the workforce performance monitoring, it is required a formal consult of the authorities to understand the limits of "biometric" and clarify the objective and contextual goals of performance monitoring. Therefore, it brings a discussion around the "legitimate interest in the performance" [116].

Governments play a fundamental role in proposing and managing legislation of the human vs technology game. In democratic countries across the world, legislation is a parliamentary prerogative. The trend to merge humans with computers and machines is called "Transhumanism" [117]. Inside that new transhumanist prism, political parties are being created from the United States to the UK and Germany [117]. Through a network called "Transhumanist PartyGlobal," their common intention is to use body-invasive technologies to extend or eliminate humanity's physical, cognitive, and perhaps even "spiritual" limits [117]. Based on it is expected that the political parties can become key players in the workforce AI-management regulation. Despite the GDPR, cross-world nations/institutions are working in regulations and standards, such as:

- UK, the British Standards Institute in its draft proposal on "Information Technology – Artificial Intelligence – Risk Management Standards" [18].
- Japan's METI (Ministry of Economy, Trade and Industry) has listed employment, skilling, database protection, changes needed in laws and global collaboration as main policy challenges for AI [18].
- Canada is being advised by its researchers to focus on trust, transparency and accountability as prime AI policy challenges [18].
- India's National Strategy for AI prioritises – fairness, transparency, privacy and security as the key challenges of AI over the rest [18].
- IEEE (Institute of Electrical and Electronics Engineers) Ethically Aligned Design, Version 1 and 2, a Vision for Prioritizing Human Well-being with Autonomous and Intelligent Systems [118] and the IEEE P7000™ Standards Working Groups to set the standards for the future of ethical intelligent and autonomous technologies [119,120].

The human particular interest/relationship can influence the recruitment and promoting process [121]. It happens at the workplace, and this human bias can be embedded in the development of autonomous systems by the developers' humanity. In order to avoid human bias on the development of AI solution to manage the workforce, it is needed more than a fair judgment, for example, it is essential to foster:

- A "visiting imagination" scenario were professional systems developers come to grasp with the manifold and complex value perspectives at play in a given design context [122].
- A cross-disciplinary dialogue between developers and society stakeholders to reflect upon and address questions of what factors/issues are more significant in light of which specific norms, practices, values, and cultures [122].
- Equity and fairness, the AI systems must be developed based on human values avoiding any gender or racial bias, been designed to stay away from social-oriented profiling [18].

Defining ethics has proven to be challenging both for humans and machines. Even more difficult is to assess the human bias factor in AI systems design [18,123–126]. The higher complexity comes from the uncertainty in evaluating the influence of the local culture and the people's morals on the use of innovative technologies that are directly connected with daily life.

The UK Engineering and Physical Research Council (EPSRC) through its AREA framework (Anticipate, Reflect, Engage, Act) indicates that reflexive analysis is needed in order to evaluate the possible future impacts brought by such systems [127]. Dwivedi et al. (2019) states a framework from AI (safe for human society) perspective and indicates two dimensions in an Ethics analysis; (i) Privacy and Data protection and (ii) Human and Environmental values [18].

Furthermore, professionals and corporations have established ethics codes that guide personal and institutional conduct [128]. As part of this, specific discussions directly correlate to workforce management [129–131] and information technology for decision-making and robotization [132,133].

Additionally, another specific initiative is, for example, the European Commission initiative for brain research, cognitive neuroscience, and brain-inspired computing denominated The Human Brain Project (HBP, www.humanbrainproject.eu) has developed an organisational structure to ethical management [19,127–133]. That hierarchical structure is compost by four components: the Ethics

Advisory Board, the Ethics Rapporteur Programme, the Point Of Registration for Ethics concerns (PORE), and Ethics Compliance [19,127–133].

At the same time, the Professional Terms convey a sense of value, which reflects in a positive professional image [134], the Personal Value and Morals are developed gradually through interactive involvement with different authoritative figures (e.g. parents, teachers, mentors) [135]. Furthermore, the data ownership (employers/employees) is a big challenge [136], it is increasingly becoming a public concern to know whether the technology solutions for trusted data sharing and linkage are reliable [137].

Essentially, people are providing data that will be used for analysis and efficiency development. This means that there are a moral obligation and cultural influence on the process of performance measurement. Therefore, it is needed to understand the way people make decisions and how this relates to the social system they are operating in.

The theory of planned behaviour is a theory that connects individual decision making to beliefs [138]; behavioural (a consequence of actions), normative (what is expected) and control (what affects behaviour) beliefs all generated with personal and social influences. Reiterating this nature of the decision-making process, decisions are acknowledged to be a social process where people think about others' expectations in their social system [139].

The employment relationship can be negatively affected by monitoring/surveillance if it is used is not managed appropriately, or there is a lack of trust [140]. A fundamental phenomenon here is trust. Two types of trust most relevant are system-based trust and cognition-based trust [141,142]. System based trust attributes to trust in the way that the data will be used; the policies, frameworks and methods used to make use of the data. Whereas cognition-based trust refers to the individual's trust in the people using the data. Both types of trust are necessary and developing these starts with the employer valuing trust [140–143].

On the other hand, the use and implementation strategy of monitoring can also impact the trust between employee and employer, therefore influencing the harmony in the workplace [140]. This suggests that the employer is a crucial stakeholder in the process of using monitoring technology as both risks to the employer and employee depend on the action of the employer.

3.3 TECHNOLOGICAL ASPECTS

Information regarding the performance of workers can be transacted through blockchain technology. As well, smart contracts based on this technology can govern business between workers-companies, companies-companies. A collaborative economy [144] could start in the Construction industry utilizing the Smart Contract (Blockchain). A smart contract can be automatically conducted by pre-established conditions triggered by a specific entity/stakeholder [145,146]. Clohessy and Acton (2019) pointed out that the blockchain technology is an alternative for companies achieves compliance with GDPR regulation on identity and data protection [110]. The integration of Blockchain and BIM can ensure change tracking and data ownership [147]. It could also make construction industry contracts more trustful and less prone to have claims/change orders [45].

Stakeholders would need to go through substantial data for quick decision-making [148]; a quick response will require powerful processing employing AI (e.g. machine learning, deep learning)

[149,150]. Personal privacy and security are challenges of global data information sharing [151–153]. Simultaneously, that new way of business operations brings embedded cybersecurity process issues [154–157].

3.4 GDPR

GDPR is the core of legislation in the European Union, and it has been influencing data regulation initiatives around the world. In the framework, essential legal information that comes mostly from the GDPR was added. As introduced before the GDPR (Rec. 155 and Art. 88) redirects employee monitoring for the Member States legislation through the collective-agreements, also Art. 22 rules of automated decision-making. On the other hand, the European Commission Opinion 2/2017 on data processing at work [158] and, the WP251 "Guidelines on Automated individual decision-making and Profiling" [159] also bring statements that are connected to the proposed framework regarding direct workers management. The Opinion 2/2017 on data processing at work [158] highlights from GDPR: Art. 25 about data protection by design; Art. 35 to carry out a Data Protection Impact Assessment (DPIA); and also brings Art. 88 that endorses the previous understanding about monitoring in the workplace. However, in other aspects, it is ambiguous; it brings many thoughts over the EU Data Protection Directive (95/46/EC) that was repealed by the GDPR (wrote in 2016 and established in 2018).

The proposed combination of subjects including Electronic Performance Monitoring, Artificial Intelligence Decision-making and Smart contract (Blockchain) represents an innovation in the challenging and controversial workplace. Furthermore, demand break paradigms inside a new and vast regulation (GDPR) without judge-made law, different approaches can provide conflicting statements. A positive point of view is presented in this work, hoping that new technologies will bring benefits for both employees and employers. That remains in the legitimate interest principle, not confronting employees' fundamental rights and having presented an effective communication to provide transparency with workers' explicit consent, with the concept of data protection by design present all time [112,158,159].

Workforce performance monitoring is a reality since the latter 1800s through studies conducted by Frederick Taylor (work method) and Frank and Lillian Gilbreth (time and motion studies) [92,160]. Construction workers' are supervised and evaluated every day in the relation of safety, productivity, and work quality.

As the Guidelines on Automated individual decision-making and profiling [159] state in section IV, specific provisions on solely automated decision-making, page 23 (based on Article 22 from GDPR, page 46 [112]): "The controller must be able to show that this type of processing is necessary, taking into account If other effective and less intrusive whether a less privacy-intrusive method could be adopted means to achieve the same goal exist, then it would not be 'necessary'.

Firstly, it is clear that the monitoring and data processing is necessary and has been applied for more than one hundred years with the advent of the first and second industrial revolutions. Traditional monitoring can be very intrusive and stressful as an observer follows the worker closely while he is developing tasks and taking notes (manual monitoring) to evaluate performance. Besides, electronic monitoring avoids human malicious influence or error (increases the data sample's accuracy). For sure, the technological methods will be more accurate and more effective in the performance assessment.

3.5 REGULATION, GUIDELINES AND AGREEMENTS

The main items that come from GDPR as: Rec. (Recital), Art. (Article), WP (Working Party), GL (Guidelines). Notwithstanding, future AI standards from IEEE and other local regulations and factors were also explored and expressed in the framework. All those specifications and standards foresee agreements/contracts between employers and employees. In order to make the worker 4.0 vision more feasible, some several steps and actions must be undertaken by all agents involved in this innovation process.

Table 3.1 (GDPR-0: General package) provides evidence for the first package or an introduction to the main principles of GDPR and IEEE standards in order to guide on a review of the Local Law and regulations, emphasizing the collective-agreements and work-codes.

Table 3.1 – GDPR-0 (General package).

Item	Content/Description
Art 5	Principles relating to the processing of personal data.
Art 6	Lawfulness of processing.
Art 7	Conditions for consent.
Rec 155	Legislative Recital 155, that allows a Member State by law or collective agreements (between employers and employees) to regulate specific rules on the processing of employees' personal data in the employment context, emphasis my, the performance of the contract of employment, management, planning and organization of work, health and safety at work. As a result, the electronic performance monitoring is allowed by a previous work agreement. (Forward GDPR-3).
Art 88	The Article 88 reinforces the Recital 155. That allows each Member States have specific rules to regulate the relationship between employers and employees. (Forward GDPR-3).
Art 22*	Automated individual decision-making, including profiling. (Forward GDPR-9, about the AI decision-making). (Forward GDPR-3, about the EPM).
Rec 4	" 'Profiling' means any form of automated processing of personal data consisting of the use of personal data to evaluate certain personal aspects relating to a natural person, in particular to analyse or predict aspects concerning that natural person's performance at work, economic situation, health, personal preferences, interests, reliability, behaviour, location or movements; …"
WP 249	Opinion 2/2017 on data processing at work.
WP 251	Guidelines on Automated individual decision-making and Profiling (Forward GDPR-9, about the AI decision-making). (Forward GDPR-3, about the EPM). (Forward GDPR-8, about the Smart Contract).

(*continued*)

Table 3.1 – Continued.

IEEE P 7000	Model Process for Addressing Ethical Concerns During System Design.
IEEE P 7010	Wellbeing Metrics Standard for Ethical Artificial Intelligence and Autonomous Systems.
IEEE P 7012	Machine Readable Personal Privacy Terms.
GL 3/2019	Guidelines on processing of personal data through video devices.
GL 4/2019	Guidelines on Article 25 Data Protection by Design and by Default.
Local law	Member States Data Protection Law.
Local regulation	Collective-agreement.
Other Factors	Ethical, Moral, Culture, etc..

*[111]

Relevant guidelines regarding consent guarantees, transparency and portability are presented in Table 3.2 (GDPR-1: Guidelines).

Table 3.2 – GDPR-1 (Guidelines).

Item	**Content/Description**
WP 259	Guidelines on consent.
WP 260	Guidelines on transparency.
Rec 63*	It makes a clear caveat that subjects' information and access rights should not adversely affect such rights as the copyright protection of software.
WP 250	Guidelines on Personal data breach notification.
WP 242	Guidelines on the right to data portability.

*[111]

Table 3.3 (DOC-0: Companies documentation) brings all the documentation that must be GDPR-compliant [161] and aligned with future AI/EPM processes. To start, the Employment contracts and Company Conduct Code should be reviewed. Further, eight mandatory GDPR-documents that all companies should have, plus eight complexly documents/records that will be required because of innovation requirements. To end, six guidelines are proposed to help the accomplishment of GDPR compliance.

Table 3.3 – DOC-0 (Companies documentation).

Item	Document	GDPR	Content/Description
1	**Employment contracts**		The employment contracts must provide for the workforce the generic information about the AI and EPM process. That should indicate the specific documents that will provide all the information about the data collected (e.g. GDPR, privacy, consent).
2	**Company Conduct Code**		The conduct code must inform all the employees about the company policies in regards to personal data information. The entire workforce should be taught how to deal with personal and other people's data.
	Mandatory documents and records		***Minimum of documents and record needed to GDPR compliance***
3	Personal Data Protection Policy*	Art 24	Top-level document for managing privacy (defines the achievements).
4	Privacy Notice*	Art 12-13-14	That explains in simple words how it will process personal data of customers, website visitors, and others (usually on companies website).
5	Employee Privacy Notice*	Art 12-13-14	That explains how the company is going to process general personal data of employees (e.g. health records, identification records).
6	Data Retention*	Art 5-13-17-30	It should content: A “Policy” process (Art 5-13-17-30) describing how long a particular type of personal data will be kept, and how it will be securely destroyed. A “Schedule” (Art 30) listing all of the possible personal data and describes how long each type of data will be kept.
7	Data Subject Consent Form*	Art 6-7-9	Document to obtain general consent from a data subject to process his/her personal data (for the specific purposes of the framework it will be made in separated explicit consent documentation).
8	DPIA Register*	Art 35	The document to record all the results from the Data Protection Impact Assessment (DPIA).
9	Supplier Data Processing Agreement*	Art 28-32-82	The document to regulate data protection with a processor or any other supplier.

(*continued*)

Table 3.3 – Continued.

10	Data Breach*	Art 4-33-34	It Should content the processes of: “Response and Notification Procedure” (Art 4-33-34) who describes what to do before, during, and after a data breach. “Register” (art 33) to record all the data breaches. “Notification Form to the Supervisory Authority” (art 33) in case it has a data breach, it needs to notify the Supervisory Authority in a formal way. “Notification Form to Data Subjects” (art 34) in case of a data breach, to notify data subjects in a formal way.
	Complexly documents/records		***Considering the complexability of AI / EPM process it will demand more complexly documents and records.***
11	Data Protection Officer (Job Description)*	Art 37-38-39	The Data Protection Officer (DPO) is needed if “(a) the processing is carried out by a public authority or body, except for courts acting in their judicial capacity; or (b) the core activities consist of processing operations that require regular and systematic monitoring of data subjects on a large scale; or (c) the core activities process on a large scale special categories of data and personal data relating to criminal convictions and offences.”
12	Inventory of Processing Activities*	Art 30	This document is mandatory if “(a) the company has more than 250 employees; or (b) the processing the company carries out is likely to result in a risk to the rights and freedoms of data subjects; or (c) the processing is not occasional; or (d) the processing includes special categories of data; or (e) the processing includes personal data relating to criminal convictions and offences.”
13	Standard Contractual Clauses for the Transfer of Personal Data to Controllers /Processors*	Art 46	It is mandatory to transfer personal data to a controller outside the European Economic Area (EEA). It is mandatory to transfer personal data to a processor outside the EEA.
14	Employee Personal Data Protection Policy*	Art 24	It is similar to the top-level Personal Data Protection Policy, but this one focuses specifically on companies' employees.
15	Register of Privacy Notices*	Art 12-13-14	To control published privacy notices in different places.

(*continued*)

Table 3.3 – Continued.

16	Data Subject Consent Withdrawal Form*	Art 7	This document provides the data subject to withdraw his/her consent.
17	Data Subject Access Request Procedure / Form*	Art 7-15-16-17-18-20-21-22	A "Procedure" process (Articles 7-15-16-17-18-20-21-22) helps define who does what when a request is received. A request "Form" (Art 15) makes it easier for the data subjects and for companies to handle such requests (a clearer picture of what the data subject wants).
18	Security of personal data*	Art 32	Different types of documents e.g., IT Security Policy, Access Control Policy, Security Procedures for IT Department, Bring Your Own Device (BYOD) Policy, Mobile Device and Teleworking Policy, Clear Desk and Clear Screen Policy, Information Classification Policy.
	Guidelines		***Useful guidelines to support GDPR documentation.***
19	Data Protection Impact Assessment Methodology*	Art 35	Guideline to develop the DPIA (a very complex task in the GDPR compliance project).
20	Cross Border Personal Data Transfer Procedure*	Art 1-44-45-46-47-49	Guideline to allow the transfer of personal data outside of the European Economic Area.
21	Processor GDPR Compliance Questionnaire*	Art 28-32	Guideline applying when performing due diligence on a processor.
22	EU GDPR Readiness Assessment*		Guideline to find out the gap between what is the actual company's scenario and what the GDPR compliance requires.
23	Project Plan for Complying with the EU GDPR*		Guideline for a mid-sized to a large company in order to know exactly who is responsible for the GDPR compliance and what the deadlines are.
24	Guidelines for Data Inventory and Processing Activities Mapping*	Art 30	Guideline to help fill out the Inventory of Processing Activities Mapping document.

*[161]

New technologies must be introduced considering the subject complexity and the extension of the data to be collected (high degree of worker's monitoring). This is likely to lead to GDPR processes established within the maximum degree of control, possibly leading the appointment of DPO (Data Protection Officers) or conducting DPIA (Data Protection Impact Assessment) as structured in Table 3.4 (GDPR-2: Officers / Corporations).

Table 3.4 – GDPR-2 (Officers / Corporations).

Item	Content/Description
Art 35 (1) (3-a)	The Data protection impact assessment (DPIA) should be conducted because the particular use of new technologies (art 35 -1) and, because the systematic and extensive profiling (art 35 -3a).
WP 248	Guidelines on Data Protection Impact Assessment (DPIA) determining whether processing is "likely to result in a high risk".
WP 243	Guidelines on Data Protection Officers ('DPO').
WP 244	Guidelines for identifying a controller or processor's lead supervisory authority.
WP 263	Working Document Setting Forth a Co-Operation Procedure for the approval of "Binding Corporate Rules" for controllers and processors under the GDPR.
WP 264	Approval of Controller Binding Corporate Rules for the Transfer of Personal Data.
WP 265	Approval of Processor Binding Corporate Rules for the Transfer of Personal Data.
WP 253	Guidelines on the application and setting of administrative fines.
WP 254	Adequacy Referential.
WP 256	Binding Corporate Rules.
WP 257	Processor Binding Corporate Rules.

Differently than "traditional" monitoring, electronic methods are also intrusive. This means that the collected data can go beyond the defined target or goal, either for general data or profiled one. Consequently, as shown in Table 3.5 (GDPR-3: Electronic Performance Monitoring), the process requires a significant understanding and trust of the correlated articles and recitals of the regulation.

Workers who will develop their tasks under monitoring must receive information and training related to the devices. In addition and, in light of legal and ethical rules, they must provide consent to collecting data (for general or profiled purposes) related to daily tasks performed on-site. This links with the different aspects of trust mentioned above. Trustful environments must be established at a personal level between employees and employer (cognitive), as well as a system-level with the confidence on the devices and post-processing methods.

Table 3.5 – GDPR-3 (Electronic Performance Monitoring).

Item	**Content/Description**
Rec 155	See GDPR-0.
Art 88	See GDPR-0.
Rec 13	It brings a general rule and the purpose of the GDPR. That could be noted a differentiation between micro, small and medium-sized enterprises.
Rec 42	"… Consent should not be regarded as freely given if the data subject has no genuine or free choice or is unable to refuse or withdraw consent without detriment."
Rec 43	"In order to ensure that consent is freely given, consent should not provide a valid legal ground for the processing of personal data in a specific case where there is a clear imbalance between the data subject and the controller... Consent is presumed not to be freely given if it does not allow separate consent to be given to different personal data processing operations despite it being appropriate in the individual case, or if the performance of a contract, including the provision of a service, is dependent on the consent despite such consent not being necessary for such performance."
Rec 48	It rules the transmitting personal data within the group of undertakings for internal administrative purposes.
Rec 52	It rules the Union or Member State law permission to a particular processing personal data in the field of employment law.
Rec 54	“Cannot the employers use the same prerogative as the Union or Member State law to the processing of special categories of personal data may be necessary for reasons of public interest in the areas of public health without the consent of the data subject.”
Rec 97	In the private sector, the figure of a controller is needed, also it is needed a person with expert knowledge of data protection law and practices should assist the controller or processor to monitor internal compliance with the GDPR.
Rec 127	There is a prerogative of single Member State has a specific regulation where the subject matter concerns the processing of employees' personal data in the specific employment context of a Member State.
Rec 60	"...Furthermore, the data subject should be informed of the existence of profiling and the consequences of such profiling. Where the personal data are collected from the data subject, the data subject should also be informed whether he or she is obliged to provide the personal data and of the consequences, where he or she does not provide such data. ..."
Art 9	It is not allowed any type of personal segregation.
Art 30	It statement all that obligations of records of processing activities.

(*continued*)

Table 3.5 – Continued.

Art 47	It regulates the binding corporate rules that allow approving of binding corporate rules cross all the enterprise.
WP 251	Because EPM is profiling it would be observe the Guidelines on Automated individual decision-making and Profiling.
IEEE P 7001	Transparency of Autonomous Systems.
IEEE P 7002	Data Privacy Process.
IEEE P 7005	Standard on Employer Data Governance.
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2.

There is a perception that EPM, in most cases, can be assumed to be a form of profiling. The same collected data may be used for several purposes, either related to the worker or the environment where he/she is working. Profiling occurs when the biometric data collected has the purpose of uniquely identifying a natural person for assessing different aspects, as the way a task is performed, safety behaviours, quality of work, effort, fatigue.

This document is mandatory to clearly inform which aspects are to be evaluated and when the data will be collected. In addition, the existence of workers' profiling should be indicated. As shown in Table 3.6 (DOC-1: Worker Explicitly Consent - 1), it could be formatted in a single document and with the essential information to take into consideration.

Table 3.6 – DOC-1 (Worker Explicitly Consent - 1).

Item	GDPR	Content/Description
1	DOC-0	Many pieces of information are contained in the package DOC-0, which all should be connected to avoid duplication of documentation.
	Art 7	"2 … the request for consent shall be presented in a manner which is clearly distinguishable from the other matters, in an intelligible and easily accessible form, using clear and plain language. ..." and "3 The data subject shall have the right to withdraw his or her consent at any time. ..."
	Art 9	For the processing of special categories of personal data it must avoid the prohibitions Art 9 (1) not connected with the outcomes (productivity, safety, health, quality, inside the work space).
	WP 249	Opinion 2/2017 on data processing at work.
	WP 251	Guidelines on Automated individual decision-making and Profiling.
	GL 3/2019	Guidelines 3/2019 on processing of personal data through video devices.
	WP 259	Guidelines on consent.
	WP 260	Guidelines on transparency.

GDPR states that just the requested and consented data should be transmitted and stored as long as necessary in a standard ontology, as presented in Table 3.7 (GDPR-4: DATA - Transmission and Storage). When processing the workforce data, there should be an evaluation of the risks of processing that data, as shown in Table 3.8 (GDPR-5: DATA - Processing). In addition, the processing must avoid any type of segregation by algorithmic bias.

Table 3.7 – GDPR-4 (DATA - Transmission and Storage).

Item	**Content/Description**
Art 5 (1) (e-f)	"(e) kept in a form which permits identification of data subjects for no longer than is necessary for the purposes for which the personal data are processed; personal data may be stored for longer periods insofar as the personal data will be processed solely for archiving purposes in the public interest, scientific or historical research purposes or statistical purposes in accordance with Article 89(1) subject to implementation of the appropriate technical and organisational measures required by this Regulation in order to safeguard the rights and freedoms of the data subject ('storage limitation'); (f) processed in a manner that ensures appropriate security of the personal data, including protection against unauthorised or unlawful processing and against accidental loss, destruction or damage, using appropriate technical or organisational measures ('integrity and confidentiality')."
Art 25 (2)	"The controller shall implement appropriate technical and organisational measures for ensuring that, by default, only personal data which are necessary for each specific purpose of the processing are processed. ..."
Art 30(5)	Position Paper on the derogations from the obligation to maintain records of processing activities.
IEEE P 7007	Ontological Standard for Ethically driven Robotics and Automation Systems.
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2.

Table 3.8 – GDPR-5 (DATA - Processing).

Item	**Content/Description**
Rec 33	"It is often not possible to fully identify the purpose of personal data processing for scientific research purposes at the time of data collection. Therefore, data subjects should be allowed to give their consent to certain areas of scientific research when in keeping with recognised ethical standards for scientific research. Data subjects should have the opportunity to give their consent only to certain areas of research or parts of research projects to the extent allowed by the intended purpose."
Rec 43	see GDPR-3
Rec 63*	see GDPR-3

(*continued*)

Table 3.8 – Continued.

Rec 75	"The risk to the rights and freedoms of natural persons, of varying likelihood and severity, may result from personal data processing..."
Rec 76	"The likelihood and severity of the risk to the rights and freedoms of the data subject should be determined by reference to the nature, scope, context and purposes of the processing. Risk should be evaluated on the basis of an objective assessment, by which it is established whether data processing operations involve a risk or a high risk."
Rec 78	"The protection of the rights and freedoms of natural persons with regard to the processing of personal data require that appropriate technical and organisational measures be taken to ensure that the requirements of this Regulation are met..."
Rec 83	"In order to maintain security and to prevent processing in infringement of this Regulation, the controller or processor should evaluate the risks inherent in the processing and implement measures to mitigate those risks, such as encryption..."
IEEE P 7003	Algorithmic Bias Considerations.
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2-3-4.

*[111]

When the collected data is used to fulfil the construction base of information (BIM), data will be shared with third parties, and all GDPR regulations on this subject must be evaluated as presented in Table 3.9 (GDPR-6: BIM).

In addition, as the process of Smart Contract is connected with third parties, only the specific and authorised stakeholder should receive its part of data. Table 3.10 (GDPR-7: Blockchain) presents the GDPR required prerogative of transparency, and Table 3.11 (GDPR-8: Smart Contract) shows GDPR concerns about profiling and sharing the information.

Table 3.12 (DOC-2: Worker Explicitly Consent - 2) evidences the Worker Explicitly Consent number two, that is correlated with the information collected, stored and shared with third parties using BIM.

Finally, Table 3.13 (DOC-3: Worker Explicitly Consent - 3) presents the Worker Explicitly Consent number three. It must be very transparent which rules will be automated and played in the Smart Contracts as well as the rights of the party/subject to review that process.

Table 3.9 – GDPR-6 (BIM).

Item	**Content/Description**
Rec 9	"'recipient' means a natural or legal person, public authority, agency or another body, to which the personal data are disclosed, whether a third party or not..."
Rec 10	"'third party' means a natural or legal person, public authority, agency or body other than the data subject, controller, processor and persons who, under the direct authority of the controller or processor, are authorised to process personal data;..."
Rec 47	"The legitimate interests of a controller, including those of a controller to which the personal data may be disclosed, or of a third party, may provide a legal basis for processing, provided that the interests or the fundamental rights and freedoms of the data subject are not overriding, taking into consideration the reasonable expectations of data subjects based on their relationship with the controller..."
Rec 69	"Where personal data might lawfully be processed because processing is necessary for the performance of a task carried out in the public interest or in the exercise of official authority vested in the controller, or on grounds of the legitimate interests of a controller or a third party, a data subject should, nevertheless, be entitled to object to the processing of any personal data relating to his or her particular situation. It should be for the controller to demonstrate that its compelling legitimate interest overrides the interests or the fundamental rights and freedoms of the data subject."
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2-3-4-5.

Table 3.10 – GDPR-7 (Blockchain).

Item	**Content/Description**
WP 260	Guidelines on transparency
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2-3-4-5-6-9.

Table 3.11 – GDPR-8 (Smart Contract).

Item	**Content/Description**
WP 251	Oversee that, because it is an automated rule and also it could be carrying some profiling. Guidelines on Automated individual decision-making and Profiling.
WP 260	Guidelines on transparency.
Rec 9	See GDPR-6.
Rec 10	See GDPR-6.

(*continued*)

Table 5.11 – Continued.

Rec 47	See GDPR-6.
Rec 69	See GDPR-6.
Art 22 Rec 71*	"The data subject shall have the right not to be subject to a decision based solely on automated processing".
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2-3-4-5-6-7-9.

*[18,109,111]

Table 3.12 – DOC-2 (Worker Explicitly Consent - 2).

Item	GDPR	Content/Description
	DOC-1	See that all the information about EPM (profiling).
1	Supplier Data Processing Agreement*	The document to regulate data protection with a processor or any other supplier. Art 28-32-82
	Third parties	Codes of conduct and specific agreements between third parties should be delimited in order to provide the privacy of the data and the strict use in which it has consented.

*[161]

Table 3.13 – DOC-3 (Worker Explicitly Consent - 3).

Item	GDPR	Content/Description
	DOC-2	See that all the information about EPM (profiling) and Third Parties agreements.
1	Execution of pre-established rules	That workforce's information provides which will allow playing specific processes between Employers and Employees or third parties.
	Payments	That could be generated directly payments between Employers and Employees or third parties.

If the AI decision-making process is well regulated with GDPR and also through the IEEE standards, this will provide requirements for machine intelligence systems, as shown in Table 3.14 (GDPR-9: AI decision-making).

A human review process is required based on GDPR Article 22 and Recital 77, as presented in Table 3.15 (GDPR-10: Human review). The AI decision-making process should be consented by the employees, as evidenced in the Worker Explicitly Consent number four; Table 3.16 (DOC-4: Worker Explicitly Consent - 4).

Finally, Table 3.17 (GDPR-11: Audit) addresses the contents to reference in an Audit process.

Additional information can be found on (https://edpb.europa.eu/our-work-tools/general-guidance/gdpr-guidelines-recommendations-best-practices_en) e.g. Recommendation 01/2019; Guidelines 2/2019; EDPB Guidelines 1/2019; EDPB Guidelines 4/2018; EDPB Guidelines 3/2018; EDPB Guidelines 2/2018; EDPB Guidelines 1/2018 [162].

Table 3.14 – GDPR-9 (AI decision-making).

Item	**Content/Description**
Art 22 Rec 71*	See GDPR-8.
WP 251	The Guidelines on Automated individual decision-making and Profiling brings concepts of: Article 5(1)(a-b-c-d-e); Article 6(1)(a-b-c-d-e-f); Article 9; Articles 13/14/15/16/17/18/21; Article 22; Articles 13(2)(f), 14(2)(g), 15(1)(h).
Art 13 Art 14 Art 15**	Of particular interest in an AI context, however, are Articles 13(1)(f), 14(1)(g) and 15(1)(h) in conjunction with Article 22 GDPR that provide for information and access rights in case of 'automated decision-making'. Accordingly, the data subject is to be provided with 'meaningful information about the logic involved, as well as the significance and the envisaged consequences of such processing'.
Art 12***	Regulation (EU) 2016/679 on the protection of natural persons with regard to the processing of personal data and on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation) [2016] OJ L119/1, Arts 12, 14 and 22.
Art 34	Communication of a personal data breach to the data subject.
IEEE P 7006	Standard on Personal Data AI Agent Working Group.
IEEE P 7008	Standard for Ethically Driven Nudging for Robotic, Intelligent and Autonomous Systems.
IEEE P 7014	Standard for Ethical considerations in Emulated Empathy in Autonomous and Intelligent Systems.
Integrating past information	In order to develop an integrated system it should be conducted an integration with past requirements presents before on GDPR-0-1-2.

*[18,109,111], **[109,111],***[109]

Table 3.15 – GDPR-10 (Human review).

Item	**Content/Description**
Art 22 Rec 71*	See GDPR-8

*[18,109,163]

Table 3.16 – DOC-4 (Worker Explicitly Consent - 4).

Item	GDPR	Content/Description
	DOC-1	See that all the information about EPM (profiling).
1	WP 251	Guidelines on Automated individual decision-making and Profiling.
	WP 249	Opinion 2/2017 on data processing at work.

Table 3.17 – GDPR-11 (Audit).

Item	Content/Description
GDPR	Values, Impacts, Wellbeing, Fairness, Equality, Transparency, Consent, and others issue.
Local law	Member States Data Protection Law.
Local regulation	Collective-agreement.
Other Factors	Ethical, Moral, Culture, etc.
IEEE P standards projects	Work in progress to standard AI and data subjects.
ISO 27001*	Internal Audit Procedure, ISO 27001 Internal Audit Checklist.
Lessons Learned	E.g. Human Brain Project.**

*[161], **[19,127]

3.6 WHAT DO PEOPLE THINK ABOUT EPM AT WORK?

Realizing workers' reaction to electronic monitoring is a crucial element in achieving successful technological innovations at the service fronts [164–170]. Because of that, a survey was conducted to understand better peoples' reaction against electronic monitoring at work.

3.6.1 SAMPLE

A total of 8914 people received the questionnaire, where:

- 8478 - Students of the Faculty of Engineering of the University of Porto (FEUP);
- 16 - Professors of the civil construction department FEUP;
- 420 - People from this researcher's network (mainly from Linkedin social network).

A total of 261 people answered the questionnaire that determining a response rate of 2.93%. Based on the population (8478) and sample (261), within a confidence level of 95% (P = 0.5), the accuracy of the responses reached an index of ± 6.3% [171]. The collected data were tabulated in MS-Excel for analysis and graphical development. Furthermore, the IBM SPSS system was used for the univariate and multivariate statistical analysis. Finally, the results were discussed comparing similar research

conducted by the insurance company AIG (American International Group, Inc.) in nine countries with 400 employees and 250 entrepreneurs in the year 2016 [136].

Young Portuguese students gave the most significant number of answers from Engineering in Information Technology and Computers, Civil Engineering, Mechanics, Metallurgy and Materials Engineering. As presented in Figure 3.1, 67% of respondents are students, 13% study and work, in effect, 80% of the sample is currently a student. It is worth noting that the vast majority of these, 58% attend the integrated master's degree, followed by 16% to develop degrees, 15% for doctorates and 10% for master's degrees.

Regarding the field of activity (academic/professional), it was identified that most of the respondents are from technology and computing fields with 43%, followed by 24% of civil engineering, mechanics, metallurgical, and materials, see Figure 3.2.

As for the gender, there was 64% male, 35% female, and 1% of respondents who chose not to be identified by a specific gender. Moreover, as seen previously, the more representative public sampled are students predominantly youngs, with 34% between 16 and 21 years old and 33% between 22 and 25 years old (see Figure 3.3). However, the sample represents the perception of future engineers who are going to entering the labour market in the coming years. Finally, as the analysis in Figure 3.4, 87% of the respondents live in Portugal, 10% are Brazilian residents, among other countries with 1% and less than 1% representation.

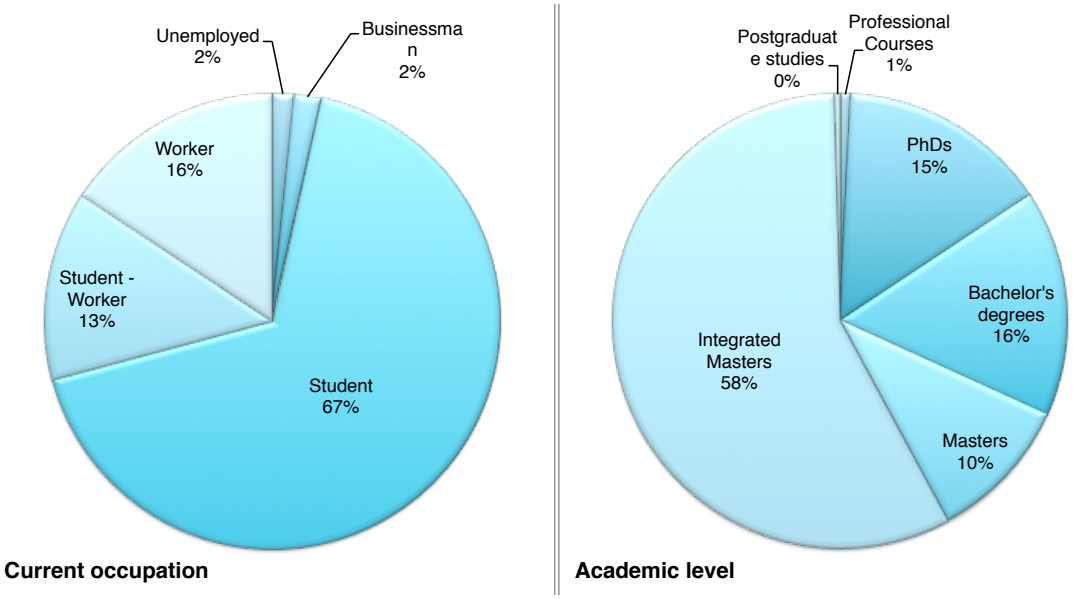


Figure 3.1 – Current occupation and academic level.

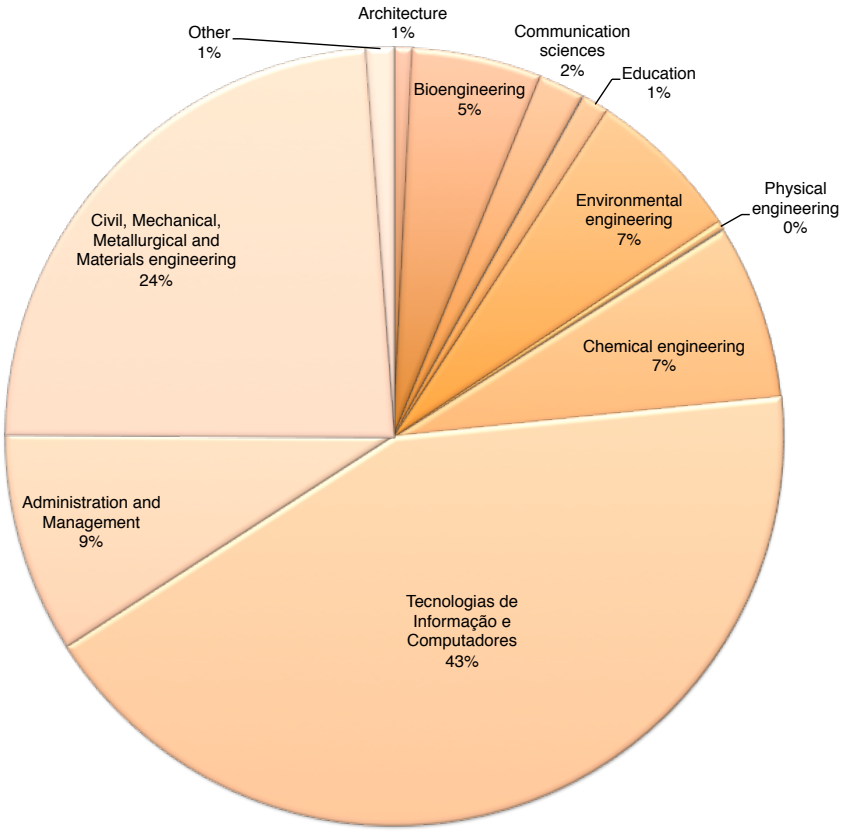


Figure 3.2 – Activity field.

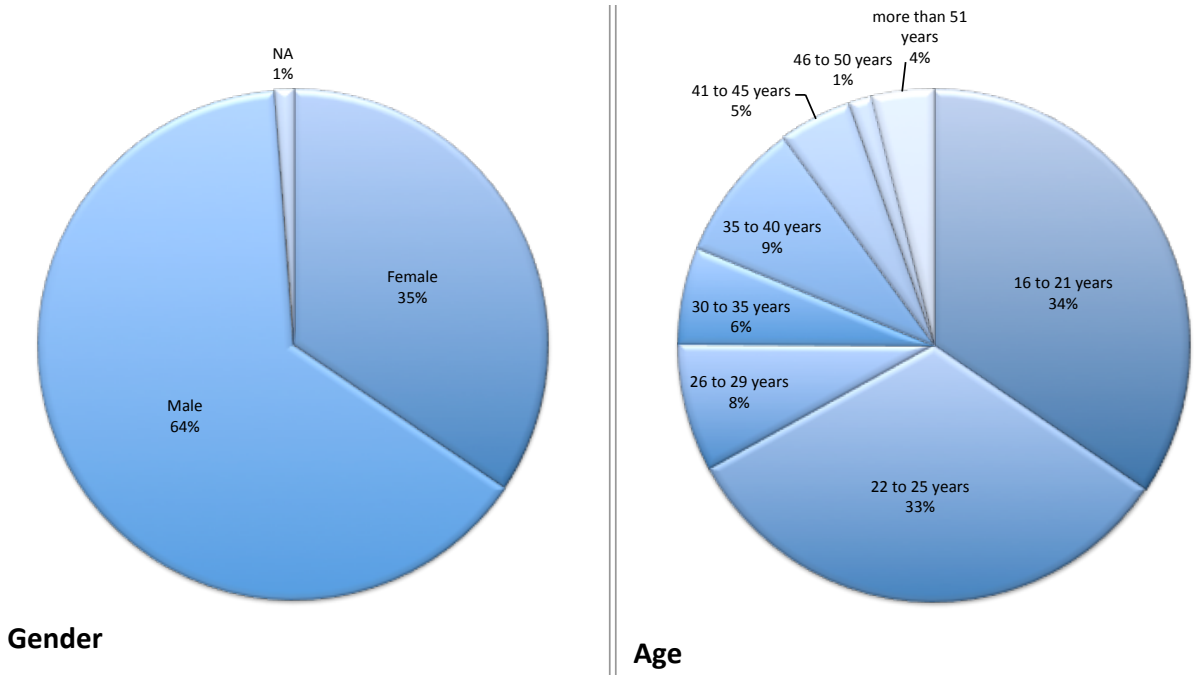


Figure 3.3 – Gender and age.

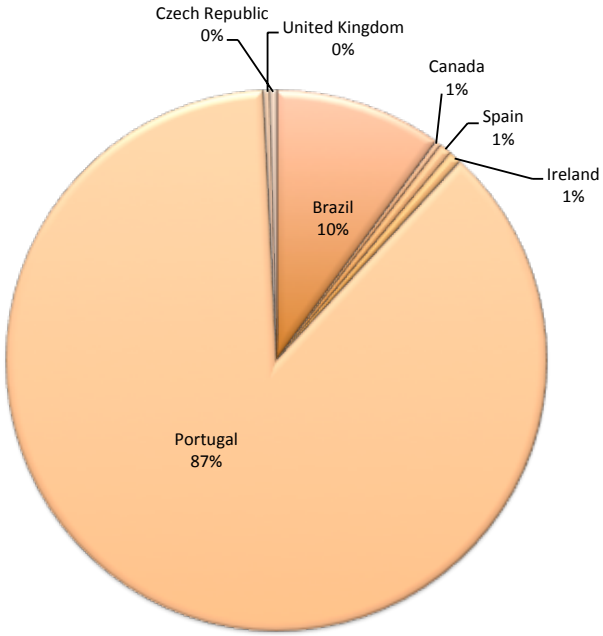


Figure 3.4 – Country of residence.

3.6.2 ANSWERS, RESULTS AND DISCUSSIONS

In order to conduct the respondents for real situations about the application of electronic monitoring at work, fourteen situational questions were applied. Moreover, two questions sat the respondents in the position of employer and twelve as workers. Besides, interviewees' personal view-positioning was observed in two questions about believing that monitoring their own work is essential to improve performance and if the government should regulate EPM. Finally, in order to identify whether or not the respondents had already had any knowledge about the EPM subject, one question was made. The results of these seventeen questions are following presented and discussed in the exact order developed in the survey.

Questions 1 and 3-8 were the types of yes/no answers with room for alternative/free opinions. Question 2 presents different options to agree/disagree as well as with room to write a distinguished option.

Question 1: Do you believe that monitoring the progress of activities developed during the workday is important for improving your performance?

Result: Yes 209 (80%), No 52 (20%). It is noticed that the great majority understands that monitoring is a relevant tool for the improvement of their own performance.

Question 2: By placing yourself in the position of EMPLOYER, you would want to use technological innovations to monitor. **Alternatives:** The safety of workers; The health of workers; The productivity of workers; The quality of services performed by workers; Other (field for text insertion).

Results: As shown in Figure 3.5, it is perceived that respondents would be more interested in monitoring in order: Safety of workers 200 (77%); The productivity of workers 185 (71%); The quality of services performed by employees 182 (70%); Workers' health 155 (59%); Do not monitor 5 (2%). The values in safety, productivity, and quality are close, and health monitoring is significantly below, still stand out fewer responses contrary to any form of monitoring. Compared to the survey carried out by AIG [136], it is observed that the population responding has higher interest levels, as for security (77%) compared to (59% AIG), productivity (71%) versus (55% AIG), and health (59%) versus (55% AIG).

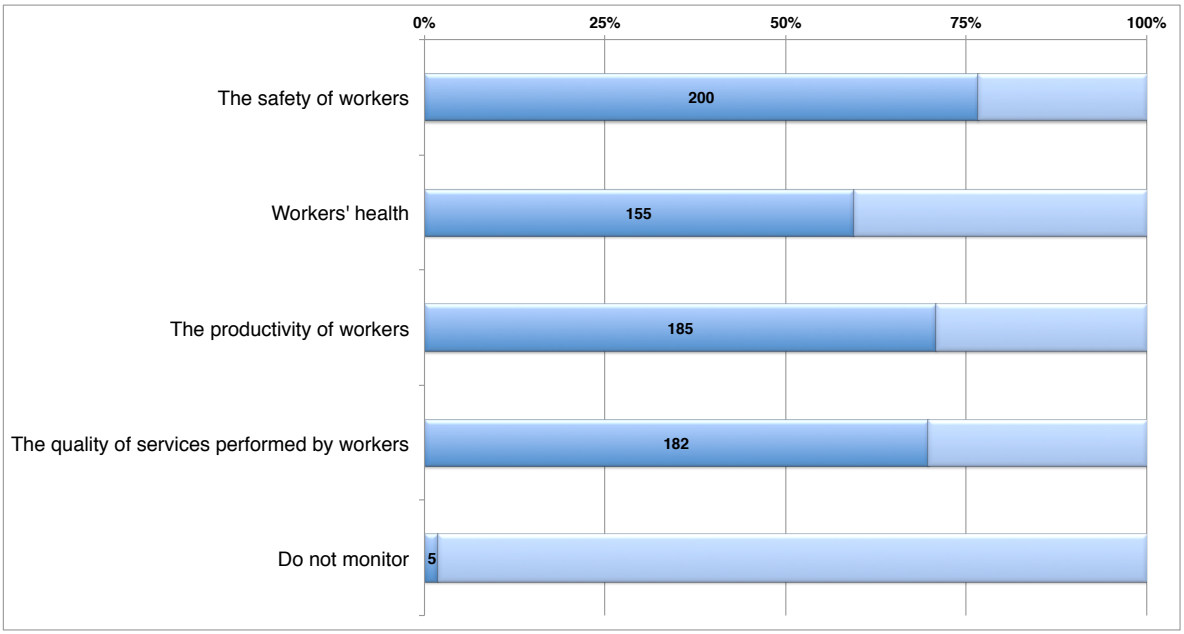


Figure 3.5 – Subjects of interest to apply monitoring.

Question 3: By placing yourself in the position of EMPLOYER, do you believe that in the case of applying the monitoring you should share this data collected with the employees?

Result: No (this information must be exclusive to the company) 47 (18%), Yes (I must allow workers access to information) 214 (82%). It is noticed that in the vast majority, people understand it necessary to share the data collected with the workers. The study conducted by AIG [136], evaluated the intention to share data of employees and employers, where per country:

- Japan - employees (80%), employers (65%);
- United States of America - employees (75%), employers (65%);
- Australia - employees (74%), employers (65%);
- Singapore - employees (76%), employers (69%);
- United Kingdom - employees (74%), employers (68%);
- Italy - employees (87%), employers (85%);
- Germany - employees (70%), employers (70%);
- China - employees (93%), employers (97%);
- France - employees (66%), employers (76%). (Abbott, 2016)

There is an alignment of the sample surveyed regarding the sharing of data, mainly that countries with higher indexes of intention to share as Japan and Italy.

Question 4: Do you believe that the GOVERNMENT should regulate electronic monitoring at work?

Result: Yes, 141 (54%), No 107 (41%), Depends on the level of monitoring 4 (2%), I have no opinion 4 (2%), Other responses 5 (2%). Compared with the results of AIG's survey [136], which indicated that 89% of employers and 87% of employees understand that there should be legal regulation of monitoring [136], the rate of only 54% seems low. Because the survey sample is predominantly of young students (still out of the job market), it can assume two hypotheses for such low value. Firstly, students still do not know/fear the possible persuasive use of EPM. Secondly, as young people, they accept electronic monitoring more naturally than older generations (employees and employers).

Question 5: By placing yourself in the position of EMPLOYEE, would you allow the mapping of your location in real-time by the employer?

Result: Yes, 111 (43%), No 150 (57%). At this point in the survey, respondents are confronted with more frontal questions about electronic monitoring methods at work. Of effect, it can perceive some greater reactivity from the respondents regarding EPM, in this specific case of allowing the mapping location in real-time.

Question 6: By placing yourself in the position of EMPLOYEE, would you allow the mapping of your movements/motions (trunk, legs, arms and hands) by the employer?

Result: Yes, 86 (33%), No 175 (67%). Within the same analysis performed previously, and, specifically regarding the monitoring of the movements and gestures, the respondents' significant reactivity was identified. This sentiment is aligned, for example, with the journalistic material published on CNN Tech, regarding the controversial patent application by the Amazon company with the intention of monitoring the workers' arms motions [172].

Question 7: By placing yourself in the position of EMPLOYEE, would you allow the mapping of your physical conditions (electrical activity of the brain, temperature, pressure, heart rate, etc.) by the employer?

Result: Yes, 138 (53%), No 123 (47%). Given the two previous answers, the monitoring of physical conditions reached a higher rate of acceptance. One possible hypothesis is that the respondents connect the monitoring of physical conditions to health issues, and in the opposite, the two previous to productivity issues. However, it should be noted that monitoring these physiological aspects could undoubtedly be used to assess productivity. As an example, in China, monitoring workers brain electrical activities to increase productivity is already a reality [173].

Question 8: By placing yourself in the position of EMPLOYEE, would you feel safe sharing the data collected by wearable electronic devices with the employer?

Result: Yes, 143 (55%), No 118 (45%). It is identified that more than half of the respondents would trust their data to the employer. However, the survey carried out by AIG regarding the employees' intention to share the data indicates higher indexes of the order of 66% to 93% [136].

Questions 9, 10, and 11 requested a situational opinion, as employees, if they were prone to allow the monitoring receiving some rewards. Meanwhile, questions 12 and 13 try to perceive awareness about safety and health in the workplace. Smartphone data collection/analysis are current issues, questions 14 and 15 asked if they would share data from their own device, and also in case of that device was from the company. Question 16 puts respondents against the wall, asking if their job depends on the acceptance of EPM if they would allow it. Finally, last question 17 asked if they knew before that survey, about those EPM methods at the workplace.

Question 9: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would allow monitoring as long as I received financial compensation.".

Question 10: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would allow monitoring as long as I received more days off as a benefit.".

Question 11: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would allow monitoring as long as this would help my hierarchical progression in the company.".

It is noticed that the respondents value more the professional career concerning other rewards as financial benefits and days off. The hypothesis that can be inferred is that the young public of the sample aims to enter the job market and to have professional success, not yet to realize the relevance of the financial benefits and times of rest, see Figure 3.6, where it is highlighted:

- 33% agree, or strongly agree to allow monitoring through financial compensation;
- 28% agree, or strongly agree to allow monitoring by receiving more days off;
- 44% agree, or strongly agree to allow monitoring through a hierarchical progression in the company.

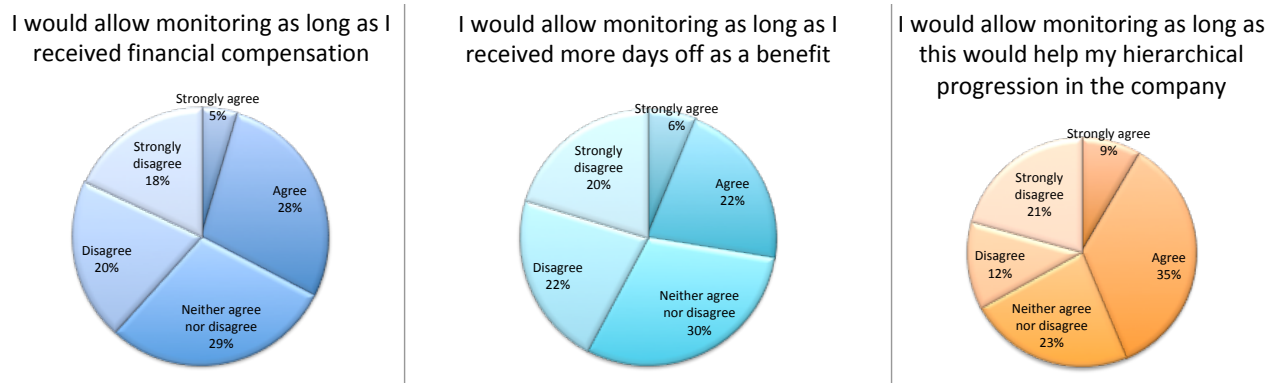


Figure 3.6 – Situation of enabling monitoring in exchange for benefits.

Question 12: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would allow monitoring only for my physical safety during the workday.".

Question 13: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would allow monitoring only in the concern to improve my physical health during the workday.".

Figure 3.7 presents the results. It can be identified that the respondents have great motivation to accept monitoring for their own safety and health, where:

- 74% agree, or strongly agree to allow monitoring in the pursuit of improving physical safety during the workday;
- 68% agree, or strongly agree to allow monitoring in the quest to improve physical health during the workday.

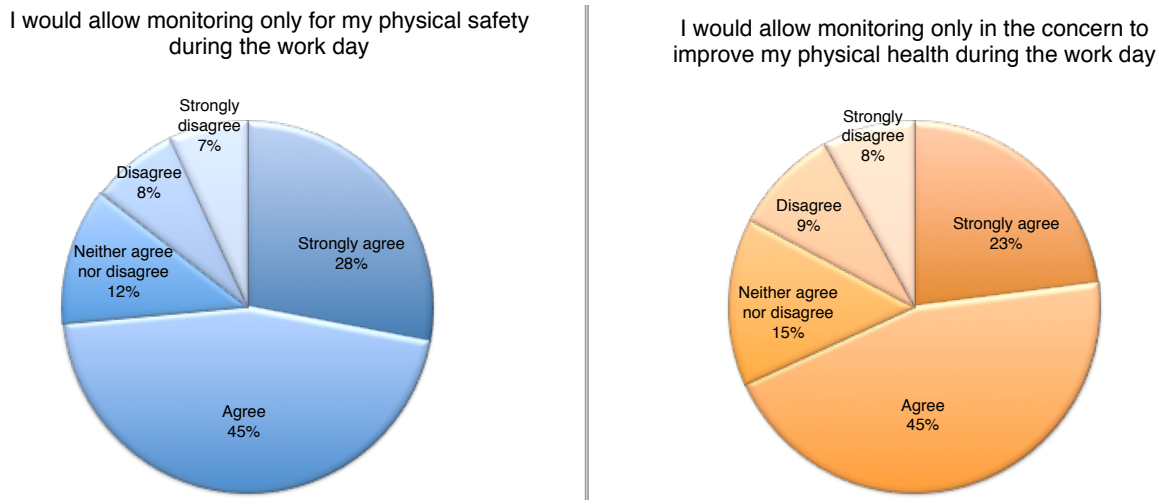


Figure 3.7 – Situation of allowing monitoring for greater safety and health during the workday.

Question 14: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would allow monitoring of data from my own smartphone.".

Question 15: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would only allow monitoring data from a smartphone provided by the company.".

Figure 3.8 presents the results. It is noticed that the respondents strongly reject the idea of allowing the availability of the data of their own smartphone. However, when employer-provided the smartphone there was a significant tendency of acceptance to share data, where it is highlighted that:

- 11% agree, or strongly agree to allow monitoring of data from the smartphone itself;
- 50% agree, or strongly agree to allow the monitoring of smartphone data provided by the company.

The study carried out by AIG [136], highlights it the favourable position of employees in using a device provided by the employer, by country as forward presented:

- Germany (29%);
- Japan (36%);
- United States of America and Australia (38%);
- United Kingdom and France (40%);
- Italy, Singapore and China (56%). [136]

It can be seen that the indices identified in this survey of 50% are above the position of several countries, being close to Italy, Singapore, and China (56%), countries with more favourable indexes.

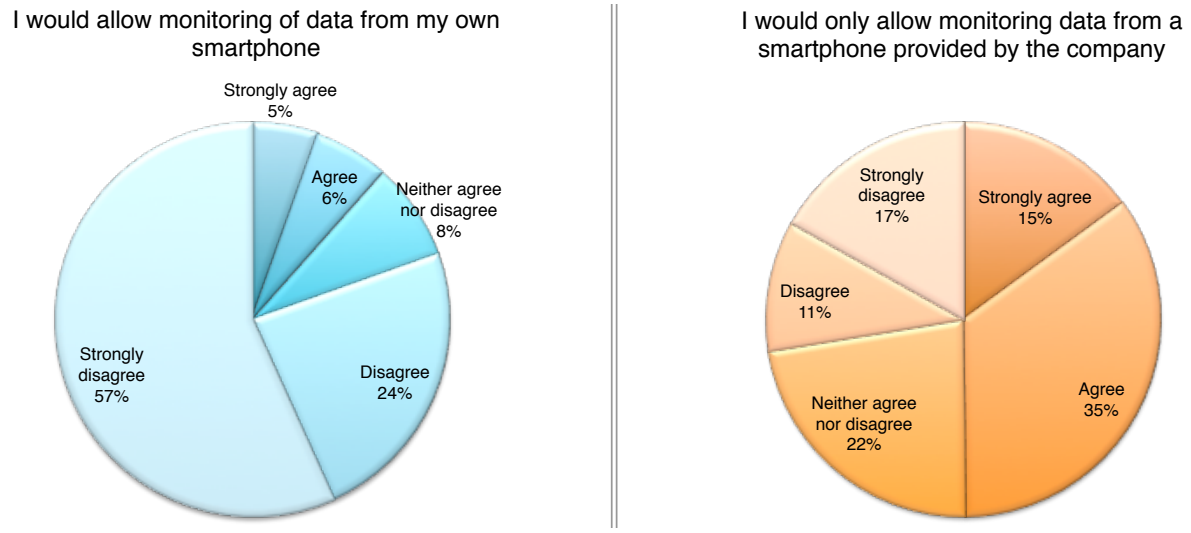


Figure 3.8 – Situation of allowing the monitoring of private and company-supplied mobile phone data.

Question 16: Regarding the monitoring by means of electronic devices and wearables, by placing yourself in the position of EMPLOYEE in these situations: "I would never allow monitoring, even if that would be a prerogative to get the job.".

It should be noted that 55% disagree, or strongly disagree with the proposed statement, which indicates that these respondents in the postulated case would accept the monitoring to access/guarantee a job vacancy. Only 14% responded by indicating that they would withdraw from the job if there were the prerogative of monitoring, where the result points out that:

- Strongly agree (7%);
- Agree (7%);
- Neither agree nor disagree (31%);
- Disagree (28%);
- Strongly disagree (26%).

Question 17: Have you had contact or knowledge of the use of electronic monitoring systems in the workplace?

Surprisingly, a large part of the respondents (69%) only have known about the subject of electronic monitoring at work through this survey. In practice, only 7% had real-life experience on EPM, and 24% knew some piece of information from some news. Where the options presented were:

- No. “I did not know the matter.” 180 (69%);
- Yes. “I've followed or participated in projects of this type.” 19 (7%);
- Yes. “I had already obtained information on the subject (internet, videos, lectures, etc.).” 62 (24%).

3.6.3 Quantitative analysis of the level of acceptance to electronic monitoring at work

An EPM level of acceptance is possible by quantifying the answers. The questions with answers of type "yes" or "no", were quantified on a binary scale, been by unfavourable added zero (0), and most favourable to the monitoring one (1), where:

- Question: 1; Yes (1), No (0).
- Question 3; No (1), Yes (0).
- Question 4; Yes (0), No (1), Depends on the level of monitoring (0), I have no opinion (0), Other answers (0).
- Question 5-8; Yes (1), No (0).

As a criterion for the question of multiple choices (question 2), one value (1) was established for each selected item. Given a value of zero (0) to the indications of not monitoring. In this question, the values have variable from zero (not monitor) to four (selection of all items), where:

- The safety of workers (1);
- Workers' health (1);
- The productivity of workers (1);
- The quality of services performed by workers (1);
- Do not monitor (0).

For situational questions with five alternatives (questions 9-15), according to the favourable or unfavourable sense of monitoring, the following values were assigned:

- Strongly agree (1);
- Agree (0,5);
- Neither agree nor disagree (0);
- Disagree (-0.5);
- Strongly disagree (-1).

Specifically for question 16, that has an otherwise-sense of agreement, the values were:

- Strongly agree (-1);
- Agree (-0,5);
- Neither agree nor disagree (0);

- Disagree (0.5);
- Strongly disagree (1).

With this, based on the above-detailed quantification, the maximum attainable value (all favourable responses) is 19 values, in counterpoint; the lowest possible value (all unfavourable responses) is -8 values. Based on the responses and values, a value-level was determined for each respondent, see Figure 3.9. Proportionally, the total spectrum was divided into four quartiles. The first with an index between 0-25% (Q0), the second between 25-50% (Q25), the third between 50-75% (Q50), and finally the fourth quartile between 75-100% (Q75).

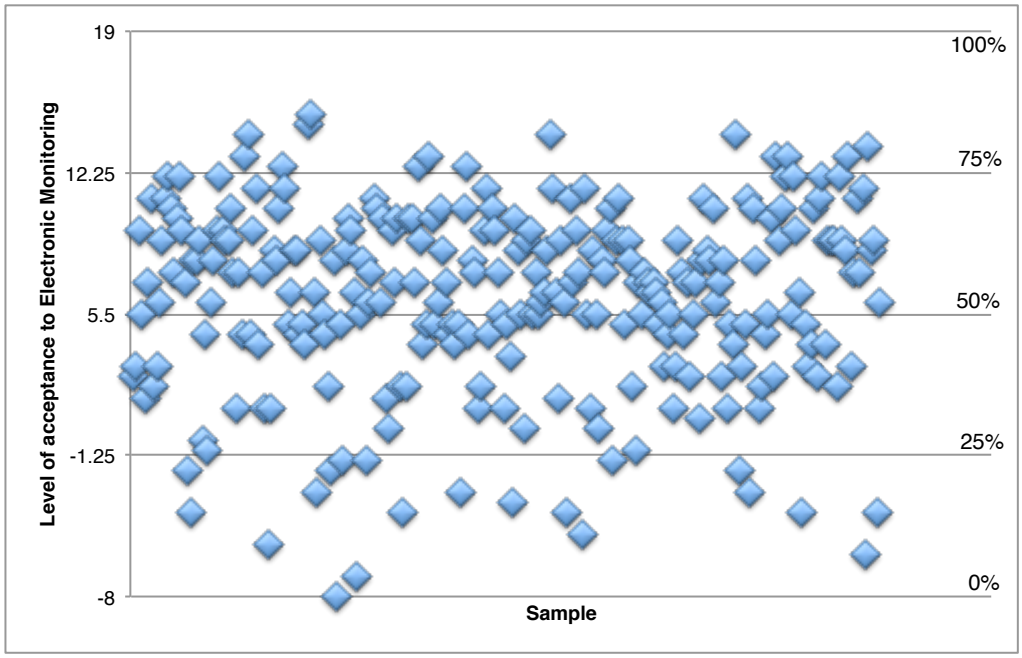


Figure 3.9 – Acceptance level for electronic sample monitoring.

It is observed that 60% of the sample (156 respondents) is in the Q50 (between 50-75%) of acceptance to the EPM. In the top quadrant, Q75, with an acceptable level greater than 75%, there are 14 respondents (5%). In this sense, it is highlighted a trend of sixty-five per cent favourable to EPM by these population under analysis. Within Q25 (25-50%) there are 71 respondents (27%). Furthermore, at the lower end, positions totally contrary to EPM, only 20 respondents (8%) were found.

Employing the SPSS software, the values and, histogram graph, see Figure 3.10, of the total sample, were determined statistically. It is observed that the average (6.3180) and the median (7.0000) have approximate values. The kurtosis value (0.3630) is below 0.5, indicating the normality of the distribution. However, the marked asymmetry (-0.7500) and the mode value (9.0000) accept the values' distribution as expected. The value that most represents the population under analysis is the median (7.0000) [174]. As other values as: Standard deviation (4.4411); Variance (19.7230); Minimum (-8,0000); Maximum (15,0000).

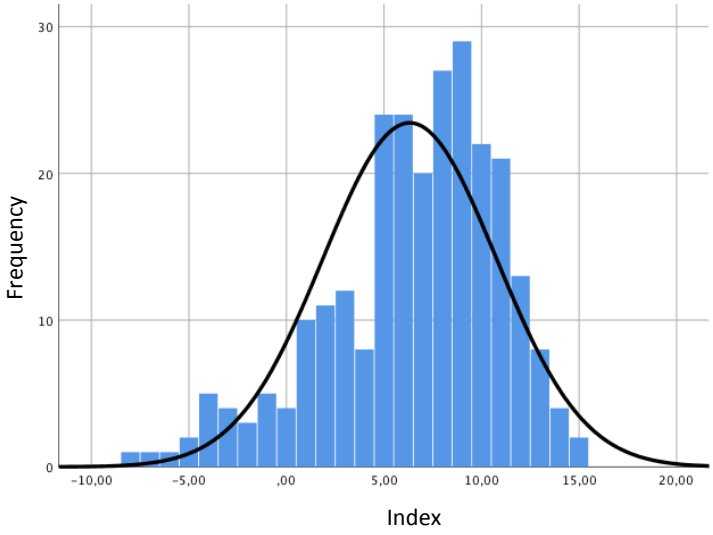


Figure 3.10 – Histogram with 261 indices of the sample.

With this, a level of 56% acceptance is determined for the electronic monitoring of the population under analysis. Within a 95% confidence level (P = 0.5), the accuracy of the responses reached an index of ± 6.3% [171].

Accounting the quartiles (Q0 - Q25 - Q50 - Q75) and the proportion of their population, Table 1, which indicate a higher or lower level of acceptance to EPM, it is possible to identify whether parameters for the sample characteristics (e.g. age, gender, etc.) can guide clusters of individuals. In this sense, multivariate statistical analysis was performed through SPSS-IBM for cluster the individuals. However, no characteristic of the sample was identified that was guiding the formation of groups of individuals, more or less favourable to the monitoring. The results and cross-analysis of sample characteristics and responses within the four quartiles (Q0 - Q25 - Q50 - Q75) are presented below. It should be noted that all values determined to vary according to the statistical error of ± 6.3%, see exemplification in Table 3.18.

Table 3.18 – Acceptance levels for electronic monitoring.

Quartile	Total	%	Lower limit	Upper limit
Q0	20	8%	1%	14%
Q25	71	27%	21%	34%
Q50	156	60%	53%	66%
Q75	14	5%	-1%	12%
Total	261			

In conclusion, the applied survey allowed a very detailed view of a population predominantly of engineers (students and workers) regarding EPM at work. An expressive level of 56% EPM acceptance was determined, and surprisingly 69% of the respondents first knew about EPM through the survey. The population under analysis is more predisposed to accept monitoring to increase safety and evaluate health. Also, reward systems (financial, days off, and hierarchical advancement) are detected as factors that may facilitate acceptance of EPM.

Raising people's awareness that monitoring makes it possible to improve performance can be a facilitating method for implementing EPM at work. However, the EPM projects' success needs to guarantee data sharing security and provide the devices for the workers.

3.7 CHAPTER CRITICAL REVIEW

As presented in this chapter, the successful implementation of EPM needs to understand what people think and obtain GDPR compliance. It is evident that applying electronic devices for the analysis of productive performance is not much perceived by people, and with a few cases of real application, there is still no jurisprudence that can guide future applications. Although there are regulatory gaps, ethical and moral gaps cannot be allowed. Workers must have full knowledge of how/for which they will be monitored and consent in advance to data collection. The barriers to EPM do not end with the presented study; on the contrary, this work seeks to foster discussion in terms of the real need to assess workers' performance and how to regulate these electronic processes better.

However, also with a focus on the successful implementation of EPM, it is necessary to understand the possible flow of information collected until its use by different systems/methods. Therefore, the next chapter seeks to understand the main KPIs that could be supplied by EPM. Also, the opinion of experts is collected regarding a possible flow of information that uses technologies such as AI for data processing.

4
INFORMATION MANAGEMENT 4.0

4.1 INTRODUCTION

This chapter presents the identification of the main KPIs that can be supplied with processed EPM information. Also, the opinion of experts is sought regarding an information flow to deal with the data collected about on-site workers. With that, the following questions will be answered:

5. How to share on-site' information with stakeholders by different systems?
6. What are the key performance indicators in construction project management?

4.2 KEY PERFORMANCE INDICATORS

It is based on the analysis of historical data of the projects that are determined by the Key Performance Indicators (KPI) and classified the best benchmarking [92]. In this context, project data on the tasks, inputs, time and human resources expended are analysed.

Depending on each company's process, these records may be contained in physical documents, or already in digital format. Nowadays, it still through human appropriation the primary process for obtaining this data in the field. Also, it is through human observation that process modelling and time studies are performed. Directly related to the analysis of the workers' performance and teams stand out the scientific models in the study of the time and the measurement of the work done [91,92].

Following are presented 13 KPIs for standardisation of performance metrics for construction workers based on electronic devices' data. First, the classic approach to measuring productivity is through input per output [22]. Furthermore, the performance indicators classified as quantitative and qualitative [175]. At the same time, the KPIs classified as objective measures and subjective measures [176,177]. Also, some aspects of the work of Adrian (2004) [91] and the safety accidents measure approach of ConocoPhillips corporation [178] are connected to the presented KPIs.

Units per Man-Hours (input per output): The quantitative analysis of the Man-Hour spends in work to performer a unit task is a measuring approach most applied in the construction industry [22,175].

Value associated per Units (input per output): Another input per output quantitative method is related to the measure of the unit of complete work per the monetary value associated (e.g. Dollar and Euro) [22,175].

On-time completion and time variation: Based on the schedule of the construction project, it identifies the finish estimated of the tasks. By measuring, completing tasks, and achieving milestones, it is possible to determine the schedule performance [175,176]. It allows the on-time completion analysis and the overview of the time variation in the estimated project [175,176].

Human resource management: The measurement of the HR spent in the construction projects is extremely important for assessment time and cost. It allows the determination of the Man-Hours expected against the Man-Hours real performed [22,175].

Quality control and rework: The quality of a construction project is related to the scope specification and features. The quality failure account in 6% to 12% of the overall expenditure Man-Hours [175,176]. The rework increases the Man-Hour needed and significantly increases the projects' overall time and cost [175,176].

Percent complete and speed of construction: The per cent complete and construction speed is the project's actual status into determinate date [175,176]. Consequently is a part of the on-time completion and time variation. Its method is widely used in measuring the monthly performed and allows a perception of the speed of the construction [175,176].

Earned Man-Hours and values: The earned value and the earned Man-hours are connected to the completed work in place [175,176]. It provides an indicator of job productivity based on the estimated Man-hours and values against that real performed [175,176].

Lost time accounting and identification: The impact factors of unproductivity are responsible for the loss of time in the construction tasks. It is essential to identify each factor and measure its impact. Most important is assessment productivity to determine qualitatively and quantitatively what are the factors that cause the most impact, both in productive activities and in the events that generate workers' idleness, which will allow the development of practical actions to modify the behaviour of a productive process [91,175].

Punch list and Extra time: Usually, the punch list approach occurs at the end of any task, phase or project. The extra time required for the workforce is another specific situation that has to be analysed [91]. As a result, quantifying that amount of Man-Hours will allow the best understanding of resource spent during a construction project [175].

Safety (accident and hazard rates): Nowadays, safety should be a significant concern in construction projects. The quantification of the work injures accidents started with work of A. W. Heinrich (1931), passing per Frank E. Bird Jr. (1969) to in 2003 a study by ConocoPhillips Marine [175,178]. Based on the ConocoPhillips Model it is connected the number of unsafe actions on-site in the way to diagnosis the potential workers' recordable injuries, lost workdays and, death fatality [175,178].

Absenteeism: A worker out of service is a Man-Hour lost. The number of lost Man-Hours due to absenteeism over the duration of the construction project should be measured to provide historical data [175].

Motivation: The understatement of the workers' motivation is significant to achieve productivity. At the same time, it is a complex and challenging assessment. A motivated worker will present the best attitude towards the tasks and the environment created on the job site [175].

Environmental Emissions: It is possible to measure CO2 and wastewater emissions based on the number of human resources (on-site and in the office) [179].

4.2.1 EPM TO ASSESS THE KPIS

Constraints are assumed as limiting factors that affect the execution/performance of a project or process. Project success (or part of it) should be measured based on pre-established terms of completing the project within the constraints of scope, time, cost, quality, resources and risk [93]. It is the prominent role of the project manager to "manage" these constraints [93].

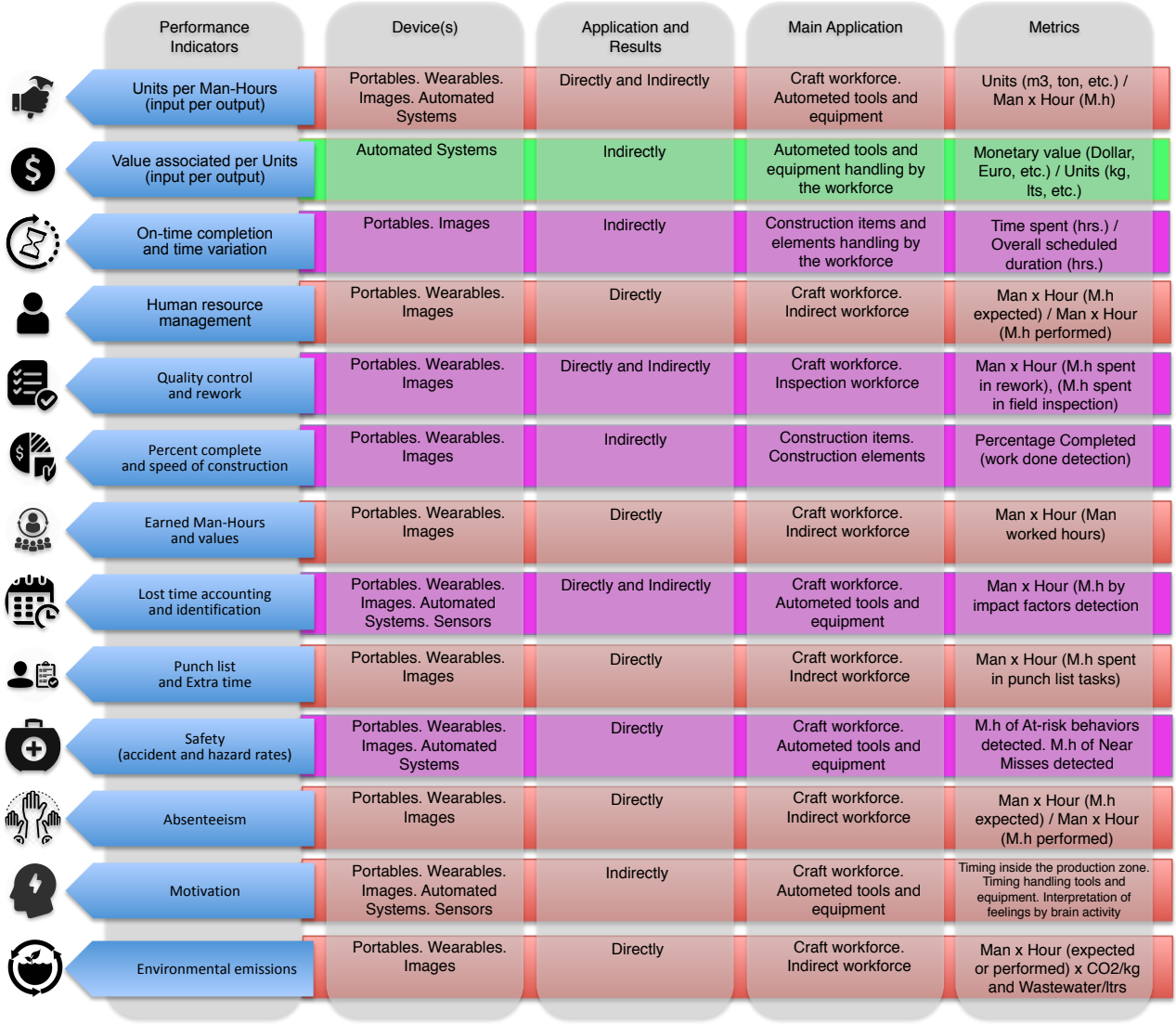
Besides these well-known overall constraints (Cost, Time, Quality and Scope/Function), construction projects are directly affected by others' safety, environment and labour productivity. Nowadays, it is mandatory in construction yards to increase the occupational safety and health performances. The International Organization for Standardization through ISO 45001:2018 established the requirements that should be implemented in projects [180]. Aspects related to climate change and environmental protection agreements have placed the environmental theme in evidence.

As a result, it can be considered another dimension of performance assessment in engineering projects [181]. Finally, the labour productivity as a fundamental engine of the construction projects drives the relationship among these other factors, in order that any poor performance in labour productivity is likely to affect the others or cause constraints.

Based on the above explanation about the data collected by electronic devices and workers' performance in the context of the standards of metrics and benchmarking. Figure 4.1 presents the framework for the standardization of electronic performance metrics [45]. Here again, colour patterns are used in the figures to illustrate the influence of innovation vectors PPT (People - in red), (Process - in magenta) and, (Technology - in green).

The concept of collecting Man-hours can be based on workers' personal identification, geolocation, trajectory, movements (gesture). Besides, the integration of information from automated tools and equipment also allows the collection of unit quantity executed. Each worker must have one device attached or be filmed and identified. This will measure the hours on duty, the motions and, the occupancy zones. At the same time, automated tools or equipment can provide the identification of the work process being executed. Further, the data obtained by sensors allows the measurement of external factors (e.g. temperature, and humidity). Based on the position, it is possible to identify the work completed on the field of the item or element. Additionally, through image analysis is possible to interpret the work completion. [45]

The electronic monitoring of construction workers can contribute to the assessment at the bottom of the ConocoPhillips Model. The At-risk behaviours and the Near Misses are the most challenging safety measurement approach as they depend on the human-observation notes usually conducted in a safety audit. Based on the location, trajectory, velocity, and use of Personal protective equipment (PPE), At-risk behaviours might be measured. Also, with the monitoring of the equipment and vehicles, it is possible to measure the Near Misses. Certainly, the IT integration allows the information about the Recordable Injuries, Working Days Lost and Fatalities. The percentage of time inside the production zone could indicate more endeavours. The amount of time handling tools and equipment could indicate more effort. The interpretation of feelings by brain activity could indicate more motivation. [45]



Performance Indicators	Device(s)	Application and Results	Main Application	Metrics
Units per Man-Hours (input per output)	Portables. Wearables. Images. Automated Systems	Directly and Indirectly	Craft workforce. Autometed tools and equipment	Units (m3, ton, etc.) / Man x Hour (M.h)
Value associated per Units (input per output)	Automated Systems	Indirectly	Autometed tools and equipment handling by the workforce	Monetary value (Dollar, Euro, etc.) / Units (kg, lts, etc.)
On-time completion and time variation	Portables. Images	Indirectly	Construction items and elements handling by the workforce	Time spent (hrs.) / Overall scheduled duration (hrs.)
Human resource management	Portables. Wearables. Images	Directly	Craft workforce. Indirect workforce	Man x Hour (M.h expected) / Man x Hour (M.h performed)
Quality control and rework	Portables. Wearables. Images	Directly and Indirectly	Craft workforce. Inspection workforce	Man x Hour (M.h spent in rework), (M.h spent in field inspection)
Percent complete and speed of construction	Portables. Wearables. Images	Indirectly	Construction items. Construction elements	Percentage Completed (work done detection)
Earned Man-Hours and values	Portables. Wearables. Images	Directly	Craft workforce. Indirect workforce	Man x Hour (Man worked hours)
Lost time accounting and identification	Portables. Wearables. Images. Automated Systems. Sensors	Directly and Indirectly	Craft workforce. Autometed tools and equipment	Man x Hour (M.h by impact factors detection
Punch list and Extra time	Portables. Wearables. Images	Directly	Craft workforce. Indrect workforce	Man x Hour (M.h spent in punch list tasks)
Safety (accident and hazard rates)	Portables. Wearables. Images. Automated Systems	Directly	Craft workforce. Autometed tools and equipment	M.h of At-risk behaviors detected. M.h of Near Misses detected
Absenteeism	Portables. Wearables. Images	Directly	Craft workforce. Indirect workforce	Man x Hour (M.h expected) / Man x Hour (M.h performed)
Motivation	Portables. Wearables. Images. Automated Systems. Sensors	Indirectly	Craft workforce. Autometed tools and equipment	Timing inside the production zone. Timing handling tools and equipment. Interpretation of feelings by brain activity
Environmental emissions	Portables. Wearables. Images	Directly	Craft workforce. Indirect workforce	Man x Hour (expected or performed) x CO2/kg and Wastewater/ltrs

Figure 4.1 – Management 4.0 KPIs [45].

4.2.2 KPIs WORKER-CENTRED

The KPIs (worker-centred) detected by sensing technologies above presented are in an interactive way connected to the main constraints of project management [45]. Project managers by controlling the construction projects based on these KPIs will be able to best-detected impacts in the project constraints, in early stages, Figure 4.2 [45].

The type of building and its function drives the needed features, and it delimits the project scope. The tasks are connected with the function and influence the specifications, allowing the determination of the environmental impact of the construction. The negative environmental impact is directly connected with the construction stage's duration in terms of pollutants, as CO2 emissions, wastewater, dust and noise.

Consequently, a more productive project is less aggressive to the environment. Labour productivity also drives the projects' time and cost [45]. In this sense, all the KPIs that measure Man-Hours are

connected with the above-cited constraints [45]. In addition, quality defects and rework will drain project resources and increase their cost and time [45]. Most importantly, safe workplace mitigates accidents and consequent absenteeism, fostering workers' motivation [45].

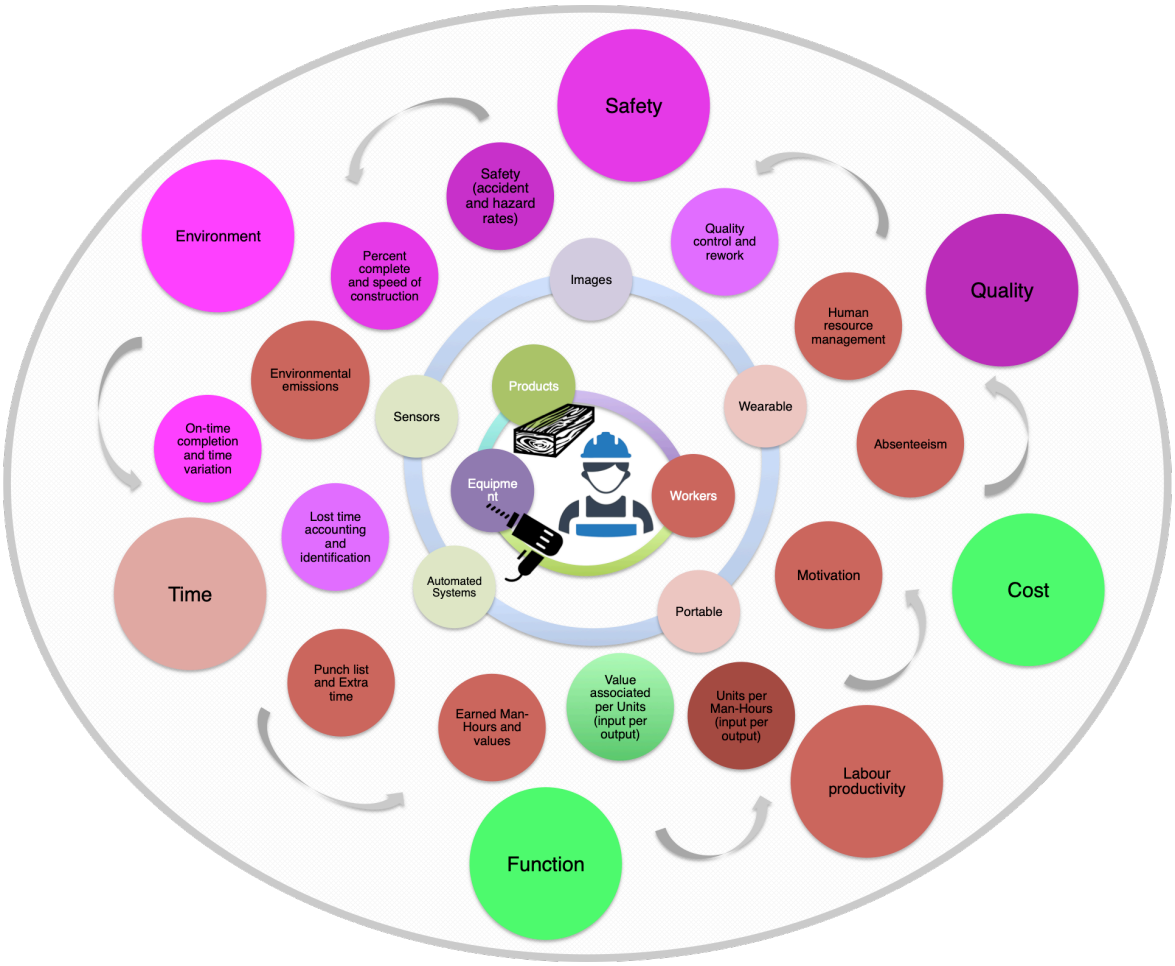


Figure 4.2 – Management 4.0 KPIs craft workforce-centred [45].

4.3 WD-BIM: THE WORKER DIMENSION

Linking extra 'dimensions' of data to information models has the potential to provide a richer understanding of a construction project [182]. BIM dimensions have been studied and developed in a way that the range of this methodology can fit the construction life-cycle [183]. The use of BIM during the construction stage was most related to scheduling and supervision, dimensions closely related to the project constraints [184,185].

The aspects related to safety and risk also relate to project constraints and are being argued if they are part of the 4D or constitute a new dimension [186]. For the purpose of this work and in respect to BIM, the workers monitoring finds links with tasks/job, schedule and safety dimensions, a part of being considered or not the same.

Following on-going research related with product information to be set during construction [187] and information strategies towards asset information management [188], COBie has been explored as the structure to support and manage all the non-graphical data. Due to this, the storage and management of relevant workers data to perform the KPI's is being envisaged using COBie Job spreadsheet combined with activities [45]. This will constitute an exciting framework for the integration of workers monitoring on BIM [189] and considering the open discussion related with the dimensions this can be found to be "WD" (Workers Dimension) [45].

Finally, a construction smart contract centred on the workforce on duty is presented. The real-time workers-KPIs monitoring fosters an automatized and transparent contract administration [45]. The whole process becomes more effective due to the automation of project updates (task order), service measurement, and payments [190].

Figure 4.3 presents the concept that underlies the construction smart contract process [45]. First, the workforce's data on daily duties is processed through information technologies and techniques, being integrated into the BIM (WD-Workers Dimension) [45]. The Blockchain system, in a private network, makes the processing and validation of this information. Subsequently, the pre-defined contract rules are automatic played, the information is shared, and specific routines are developed [45]. Most importantly, the right information will be provided for the pre-establish stakeholder without the needed of accessing the BIM tools [45].

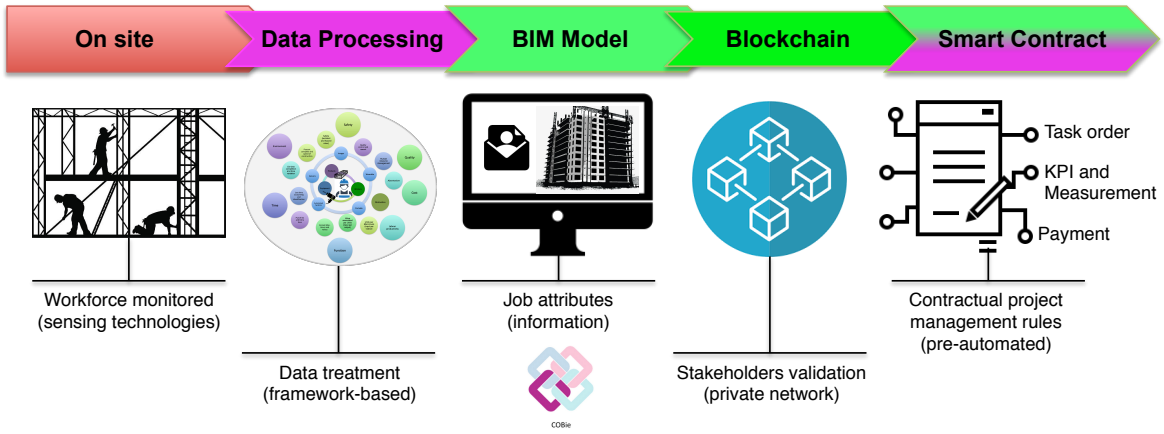


Figure 4.3 – WD - Workers Dimension [45].

Problems as unsolved claims and fast-tracking during the execution of contracts affect the finance margin of contractors. At the same time, SME cannot support late payments [190]. Due to the traceability of the most valuable information about the workforce, types of incentive fee contracts should be easier to structure. It is expected a lower risk of delays and over budgets. Furthermore, no more filtered information about poor safety conditions in the yards will be possible. Also, the BIM integration at the level of tagged build elements will allow a total quality assurance of the buildings [191].

As a result, all the construction production chain will earn more compliance and accuracy [45]. Complex projects, principal de EPC (engineering, procurement and, construction) ones will take advances on the application of the smart contract [45].

4.4 INFORMATION INTEGRATED FRAMEWORK

The Framework Core: (i) Set-up, (ii) EPM, (iii) Data transmission and storage and, (iv) Data processing; was developed considering a basic flow of start up a project to collect on-site workforce data for post-processing [38]. Before implementing it, it is necessary that the company's higher-level management commits, authorizes and sponsors the innovation project, setting the boundaries and requirements for the development of electronic control. Next, it is necessary to implement on-site infrastructure to conduct the application of the devices (hardware) with the workers.

When the system is operational (both hardware and software), the data collection begins on-site, and the analysis of this information starts being processed. The data analysis could be conducted by different methodologies based on statistical methods and AI models.

The Smart contract path was designed based on the trend to integrate the construction industry standards information (v) BIM-COBie with the (vi) Blockchain information validation to achieve (vii) Smart contracts [147,191]. As a result, the whole process becomes more effective due to the automation of project updates, service measurement and payments [190].

A collaborative contract ecosystem is possible with the distributed information from the BIM to the Blockchain ledger between the different stakeholders (e.g., client, contractor, subcontractor, vendors, suppliers, designers, consultants, insurance, bank [45]. The data information storage on BIM and through Smart contract can either be general (e.g. overall workforce worked-hours) or each worker's profiling.

The AI-management flow was developed to allow the (x) Workforce management accounting for the (viii) AI decision-making [120,131,144,148,151,192–196]. It is meant to allow the worker profile to manage specific actions. Based on the statement of the GDPR' Recital 71 (page 14): "The data subject should have the right not to be subject to a decision, which may include a measure, evaluating personal aspects relating to him or her which is based solely on automated processing…" [18,111,112], the verification process of (ix) Human review is settled.

Also, to GDPR transparency and subject data access compliance, a process of (xii) Blockchain' outputs recording was introduced, both for machine and human decision. Simultaneously, a (xi) Deep learning' calibration process was added to allow the human review's machine perception to improve the AI outputs [197].

Finally, through all the Framework stages, an (xiii) Audit process is required to assess the possible bias in the system, ensuring an ethical environment [19,127]. Figure 4.4 presents the framework for management 4.0 of the craft workers [38].

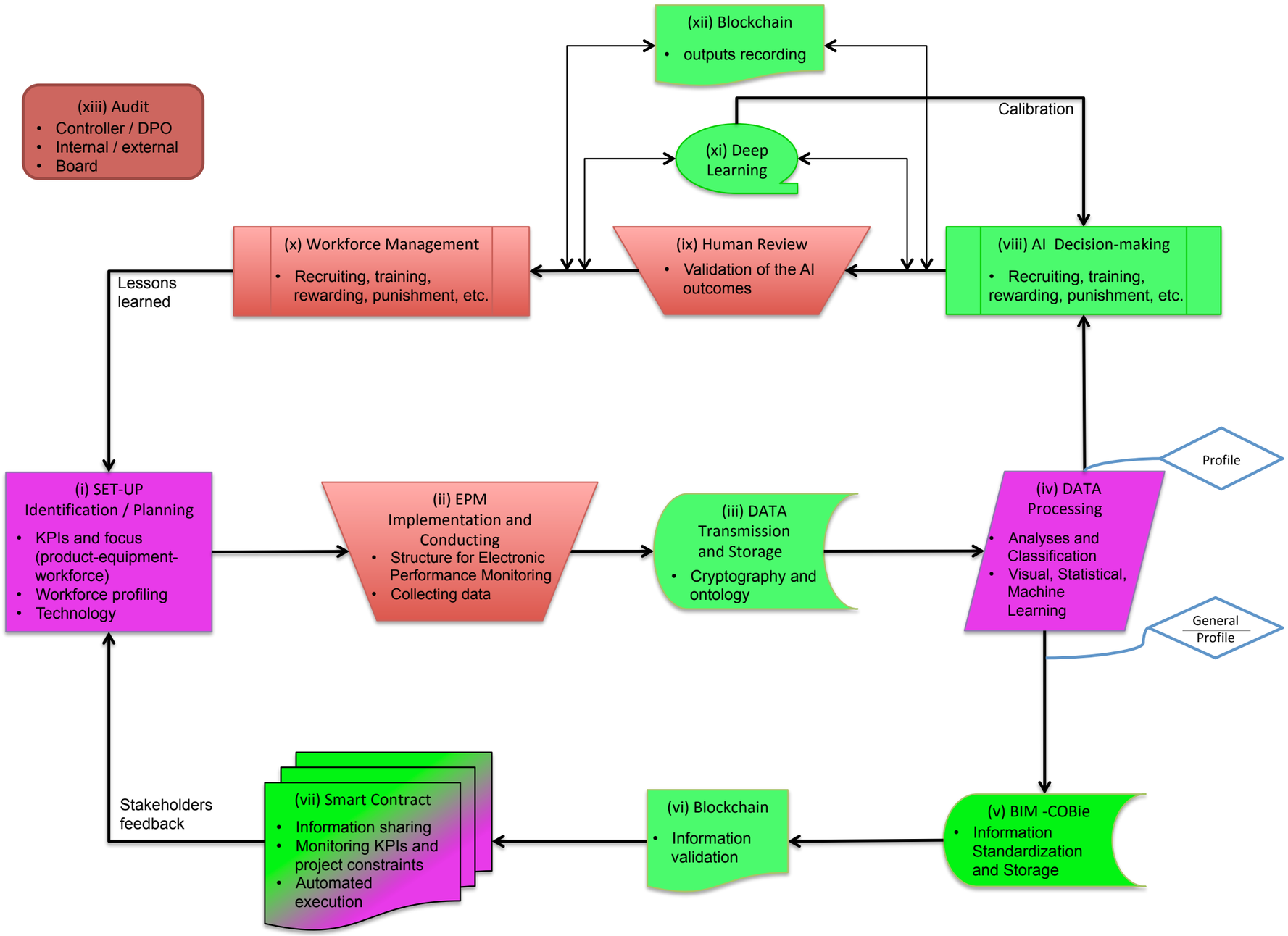


Figure 4.4 –Management 4.0: framewok [38].

4.4.1 EXPERTS' OPINION

The interviews were semi-structured and based on the framework above presented in Figure 4.4 and range several topics within the central theme. Depending on the role and background of the interviewees, specific discussions on "topics of expertise" were raised leading to the contributions that are following presented.

Table 4.1 shows the participants involved in the study.

Table 4.1 – Participants' description.

Participant number	Participant Role	Country
#1	Legal / Academic (Specialist Researcher)	i
#2	Construction Business (Senior Executive)	ii
#3	Information Technology (Senior Professor)	iii
#4	Construction Business (Specialist Executive)	iii
#5	Construction Business (Project Manager)	ii
#6	Information Technology (Project Manager)	ii
#7	Legal / Academic (Senior Consultant)	ii

4.4.1.1 Worker 4.0 benefits

#1 A framework focused on workers is a relevant topic. It can constitute a reason to start a strategic discussion within the European Commission in terms of policy development and practical case of enablers and barriers.

#4 This system/framework can provide claim mitigation and bring effective transparency in the relationships between Construction Companies and Clients.

#6 The two Blockchain gates increase transparency to the framework. It will be informing the data sets and the algorithm's code.

#4 There is no tool/product or service ready to use for this proposed framework. Customised system needs to be developed embedding all rules, processes and expertise. Given the range of the topics the development team must be multidisciplinary, constituting an even bigger challenge.

4.4.1.2 Challenges (benefits/threats)

4.4.1.2.1 GDPR and law

#2 The GDPR will be a challenge for the implementation of EPM and AI systems.

#7 For the implementation of EPM the compliance with GDPR and countries legislation (labour legislation and collective agreements) is mandatory.

#7 The Portuguese construction collective agreement does not regulate any form of workforce performance monitoring, and it should be regulated.

#7 Workforce explicitly consents is required prior to data information collection.

#6 Based on the GDPR it is necessary pre-authorization of the workforce to collected the data and to assure the transparency of the data treatment (what for).

#1 As long data is not directly targeting the profiling of the workforce, for example, measuring the process of construction as a role, or to improve planning accuracy, the GDPR shouldn't be a problem.

4.4.1.2.2 ROI (Return on investment)

#4 It will be a challenge to quantify the real benefits for the companies (buyers of these technologies), how they will have the ROI.

#4 The biggest benefit in the field of data information is the ability of collecting a great amount of data (collected for a long time) without the human interference/appropriation. This is due to the human observation that introduces noise and strain to the assessment.

#3 The big amount of data and the traffic band are technological challenges.

4.4.1.2.3 Data ownership

#2 The companies are the natural owner of the collected data. In the future, with improved awareness of the data value, Clients will request the data ownership, and it could be a big challenge.

#3 The Companies are the owners of data and sharing it will depend on the regulation (GDPR).

#4 The data ownership will be a challenge/fight, but it should provide/share benefits for all stakeholders (workers, construction companies, clients).

#5 The data ownership is to the company that pays the workers.

#1 The data ownership is quite an issue! It could be the owner, the public administration (for example, when the construction of a hospital) or the contractor. If data becomes public that can be a strategic damage for the company that developed the structure.

4.4.1.2.4 Do profiling or do not profiling? And the Design bias

#3 Individual monitoring will bring as a benefit the individual opportunity of learning.

#3 The ethics of design is more dangerous than the algorithms bias, because the algorithms bias are already widely known and easier controlled.

#6 A stakeholder heterogenic involvement (business managers, developers, HR people, etc.) as a co-creation of the system rules is very important to prevent the algorithms bias and to have the ethics in the system design.

4.4.1.2.5 Equity

#4 The AI (decision making) must be an auxiliary tool of decision; meaning that humans should do all the decision-making.

#5 The AI (decision making) process must be conducted by an outside company in order to maintain the transparency/trust of the system.

4.4.1.2.6 Productivity approach

#2 EPM main goal should be the ability to assess the construction work performance rather than the detailed assessment of the tasks (equipment and workers). It is evident that to achieve it is required to assess the different parts that constitute the construction work.

#2 The safety concern should be the driver to demonstrate the value of workforce EPM. After that, it will be easier to explain that data can be used to boost productivity.

#5 Following the measurement of the production workforce it is important to seek a way of assessing the quality of the tasks outcome (quality).

#5 The EPM implementation should be gradual and following the lessons learned, previous initiatives as safety issues. This strategic approach will streamline the EPM introduction in the construction industry.

#4 Productivity is the goal that supports the investment. Safety and quality are added-value sub-products.

4.4.1.2.7 Human barriers

#2 As all humans, workforce is resistant to changes. In addition, workers do not like to be monitored.

#4 The ethical challenge. Workers' feelings. Syndicate authorisation/interest.

#3 In order to break the technological paradigm of these types of innovation benefits should be delivered for the workforce.

#2 Electronic devices should be embedded in the personal protection equipment or in the tools/equipment to avoid additional resistance to use.

4.4.2 SUMMARY

The proposed framework establishes a sequence of flows and processes that leads to the full implementation of EPM materializing; therefore, the craft workforce's upgrade to the 4.0 assumptions/vision. It was possible to contribute to the body of knowledge by identifying enablers/barriers, gaps and requirements. The success of innovative actions relies on a balance between aspects considering technology, processes and people. All these aspects find the correspondence to the challenges as mentioned earlier, as well as the defragmented framework.

In most of the innovation processes within the construction industry, technology is usually not the most challenging part to achieve; this application is no exception. However, there are essential issues previously highlighted as the ethical aspects of software development and the trust environment required for AI and Blockchain. Regarding processes, as above detailed, GDPR can be a 'bottleneck' or a significant threat when it comes to the use of technology. Almost a nonsense, or not, when construction is being pushed towards automation and digitalization.

4.5 CHAPTER CRITICAL REVIEW

The flow of information within the scope of worker 4.0 is complex, and it is necessary to find the right balance between people, processes, and technologies. In the quest to improve the workforce's performance, it is essential to ensure the transparency and security of the information systems involved. It is necessary to know what will be measured and what information will be shared with which stakeholders to ensure a safe process for both workers and employers. Finally, after reviewed aspects about legal and technical challenges, the next chapter presents de EPM state-of-the-art regarding the leading technologies/methodologies.

5
SENSORED CONSTRUCTION SITES

5.1 INTRODUCTION

This chapter presents EPM' state-of-the-art and responses to a critical research question "7. What is the-state-of-the-art on electronic performance monitoring?". It focuses on mapping the technologies and methodologies that will populate the CI sites shortly. Firstly, the main devices and methods applied for monitoring productivity in the CI are presented. It was identified the most applied techniques in the ambit of the workers. Finally, studies on the classification of workforce activities are diagnosed. The focus of this chapter is to obtain general and specific knowledge for future EPM testing and applications.

5.2 ELECTRONIC PERFORMANCE MONITORING

5.2.1 ELECTRONIC DEVICES AND METHODOLOGIES TO COLLECT ON-SITE DATA

The electronic devices must be selected based on the company's sector of activity, considering what is sought to monitor. The combination of different technologies can bring more broad and effective results with more cost-effectiveness. Based on the complexity of implementing electronic monitoring, it requires specialized resources.

The automation of the data collection process pertinent to worker productivity focuses on the monitoring of Location; Trajectory; Movements and gestures; Time in specific action; Physiology; External factors [45,198–205]. For potential application success in the construction industry, electronic data collection devices must meet many of the criteria listed below:

- Investment - implementation and maintenance costs appropriate to the number of items to be monitored and the expected return on investment;
- Resistance and durability - robust enough to withstand a hostile environment and capable of lasting for the entire duration of the project or until reused [206], it must have energy independence allowing its long duration or appropriate recharge cycles;
- Device formatting factor - small enough to fit any resource (as needed in particular for workers) without interrupting the course of work activities [206];
- Usage and training - must have a level of complexity for operation and handle appropriate to the characteristics of end-users;
- Scalability - robust in a variety of different application locations (internal and external environments, small to large spaces, physical obstacles) [206] and, the ability to control a large number of elements at the same time;
- Reliability - able to record accurately [206];
- Data refresh rate - high-frequency data provided in real-time (greater than or equal to 1 Hz) [206];
- Transmission and storage of data - smaller specific communication infrastructure possible, smaller data volume for possible storage;

- Data security - should provide guarantees of confidentiality of data, especially where relevant to workers [206].

5.2.1.1 Portables and wearables

The portable electronic devices are considered those that are handled by workers. On the other hand, wearable devices can be inferred next to the body, that is, adhered or in clothes [207] and those coupled to workers' personal protective equipment [202,205,208,209]. Firstly, because they are close to the human body, these technologies must be provided with adequate anatomy and safety, for example, to avoid electric shocks or burns [207].

Other important issues are: aesthetics, size, resistance to bad weather and aggressive environments, energy consumption, wireless communication and usability regarding the operating system used [207]. The application of these technologies primarily focuses on monitoring the location, trajectory, movements, gestures, and physiological aspects of the workers.

The RFID technology, Radio-Frequency IDentification, is applied for identification, traceability and localization of tools [210], materials [211–213], equipment and vehicles [214,215], and workers [216–220]. Radiofrequency communication occurs basically through RFID tags (transponder or RF Tag) that have the capacity to store information internally, and which use radiofrequency fields to exchange information with readers who are equipped with an antenna.

The Ultra-wide-band UWB technology and RFID are also based on radiofrequency communication yet have better locational accuracy (less than 10 cm), making it preferable to monitor trajectory and movements. There are scientific studies that carry out applying UWB on products [221–223], equipment and vehicles [224,225] and, workers [198,226–230].

Besides, satellite navigation technology, Global Navigation Satellite System (GNSS), is based on a network of orbiting satellites that transmit high-frequency radio signals to land-based receivers with time and distance data from which to obtain their geographical position [231]. More commonly used globally, the North American system is called GPS (Global Positioning System) [231]. The great advantage of GPS is that without the need for local infrastructure, with at least four satellites, it is possible to obtain real-time positioning at a frequency of 1 Hz [232]. However, the main disadvantage lies in the fact that when in closed environments or with a large concentration of obstacles without a direct satellites view, no readings are obtained or the data is received with significant imprecision. Most of the GPS studies focus on monitoring equipment and vehicles [232–236] and workers [199,237–240].

However, RFID, UWB, and GPS technologies can be both handhelds, when on handheld devices (e.g. readers and smartphones), and being found embedded in wearable devices (e.g. badges and smartwatches).

The technology called IMU (Inertial Measurement Unit) has as its concept the use of electronic devices equipped with a battery or power supply that have the combination of sensors of the type accelerometers, gyroscopes and even magnetometers to determine the velocity, orientation and gravitational forces [241].

The devices in IMU are equipped with wireless type chips that allow the communication of the data. Smartphones already have IMU-type sensors, as well as the resources needed to transmit collected data, which makes their application more manageable in the field of the construction industry [205,241,242]. With the application of IMU devices to shoes [208,209] or ankles [243] of construction workers, the mapping of their trajectory [208] is sought, and therefore the positioning and construction of a vision in 3D are possible [209]. That also can be able to diagnose inappropriate postures of construction workers during their manual activities [244]. As well as realizing the skeletonization of the human body in 3D, with IMU devices applied in joints of the human body according to the model of rotational matrices and Euler angles [245].

The use of smartphones embody on workers (e.g., armband wearable) allows to carry out movement measurements in a manner analogous to the wearable IMU devices [205,246]. It has excellent potential for application in the construction industry as it presents an adequate cost-benefit [205]. Smartphones equipped with a specific application can be multifunctional: collecting, analyzing and transmitting data, not requiring auxiliary devices or dedicated network, and providing a graphical and audible interface for informing and interacting with users.

The fatigue of construction workers is directly related to non-productivity, loss of quality of services and increased risk of accidents [202]. The physiological aspects of the workers can be monitored, according to the parameter and type of sensor to be used [247], for example, electrocardiogram (electrodes); Heart rate (electrodes or pulse oximeter); Rate of respiration (piezoelectric or piezoresistive sensor); Body temperature (adhesive sensor); Movement of the body (accelerometers); Body orientation (accelerometers); Saturation of oxygen (pulse oximeter); Transpiration (galvanic response sensor); Electromyogram (electrodes). Knowledge of these aspects is essential for safety initiatives and the understanding of worker productivity [247].

The current technological development has strengthened the provision of wearable devices equipped with sensors to analyze individuals' physiological aspects, mainly focusing on health and sports performance. Recent scientific publications present the application of these commercial resources for the evaluation of workers in the construction industry [202,248–251]. Also, the use of more complex devices such as electroencephalogram (EEG) measures brain activity [202,252], which can be used to evaluate the workers' comportment.

In order to measure the heart rate, two sensor technologies are presented: the electrocardiogram (ECG), currently applied in wearable cases for use in the thoracic cavity [208,250,253]. Furthermore, Photoplethysmography (PPG), which is applied to wristband [248,249,253], as an example of smartwatchs [248]. The pulse devices still have the ability to analyze the motions of the arms and the count of steps employing accelerometers, inferring results such as calorie expenditure and the number of steps [248,253], still evaluating the quality of sleep [253].

Smartwatches can also monitor the skin's galvanic resistance and temperature [248]. Other sensors applied to the skin can also obtain workers' body temperature [202]. The smartphones can collect and transmit data about the body activities determined through the various technologies and sensors [241,242,254,255]. The versatility of smartphones to transmit data without the need for a dedicated communication infrastructure should facilitate the application of wearable technologies in building environments that do not yet have an IT structure.

The ECG [202,250,253], and the PPG [202,248,250,253] are able to read the heartbeat of construction workers and that not only allows an assessment of the physical state and the level of activity of each individual, but it also allows a perception about the emotions, the reactions to climatic conditions, aggressive body conditions (e.g. alcohol, drugs and sleep deprivation), in effect to provide control of the fatigue. The combination of heart rate measurements (ECG and PPG) with measurements of temperature (directly on the worker) and brain activity (EEG) enhance accuracy in the diagnosis of fatigue [202].

Also, other wearable products focusing on the quality of life and for sports monitoring can potentially be used in assessing workers' performance. Examples are the Athos device, which is technical sportswear that monitors muscular effort [256] and the Movit, a ring that monitors body movements and activities [257]. The Nuada (electronic glove) is a product developed by a Portuguese company, for the use of people in increasing hand power [258]. It can allow the evaluation of the workers' movement and the diagnosis of productive movements [258,259]. Finally, another possibility is the technological glasses like Google Glass and Microsoft HoloLens, used commercially with a focus on mixed reality (virtual elements and real image) applied in work environments [260–263].

5.2.1.2 Imaging

The construction industry needs to turn voluminous monitoring videos into concise and structured data for easy storage and analysis [264]. Nowadays, the ease in the acquisition of devices to capture images has significantly boosted the number of photos and videos that are being collected on construction sites [24].

The most applied image processing methods use colour, gradient and texture characteristics to identify materials and people [264]. Capturing and transmitting images instantly through the Internet enhances data communication and allows remote control of material and human resources on the construction sites. Monitoring equipment and workers' location and trajectories enable management in safety and productivity [265–270].

Gong and Caldas (2011) developed, based on video images, a semi-automated method for evaluating workers' productivity in productive processes in construction sites [97]. The model is based on the preliminary mapping of the production process to identify the activity execution cycles [97]. By mapping the trajectory and occupation of workers and equipment, the time spent in each determined cycle of the production process is determined [97]. The results indicate a mean accuracy between 91% and 86% in the evaluation of the process cycles and a mean accuracy between 87% and 81% in assessing the occupation of the workers [97].

Consistent tracking of multiple workers and equipment over a long period tends to be more problematic [97]. The imaging takes frequent failures due to obstacles and the crossing of the trajectory between dynamic elements [97].

A camera framing can cover a large area of a building, and a single device can perform the monitoring of several elements without the need for each entity to monitor it must have a unique device for it to be detected. Two-dimensional imaging devices are easy to handle, not providing specialized features or training to use. However, data processing techniques, both in 2D and 3D, have a high degree of complexity requiring specialized features and specific systems.

With the popularization of unmanned aerial vehicles, UAV (Unmanned Aerial Vehicle), or as commonly called drones, new academic studies in the field of the construction industry arise [271,272]. During the construction phase, the drones can have two functions: perform continuous and autonomous monitoring of the work and automate construction tasks [273].

The progress of the work performed by image systematics can be supplied with images collected by drones [273,274]. The drones can perform continuous inventory control on storage yards [273]. Furthermore, drones for viewing and inspections of high-altitude and hard-to-reach sites facilitate operations [273] and avoid human exposure to the risk of work accidents. As challenges the application of this technology is observed: the need for safe autonomous navigation in a congested internal environment [273,274], the integration of data and technologies applied in construction projects [273,274], and a large number of large resolution images collected that could generate a significant volume of data for storage [274].

Three-dimensional images can be captured through motion capture systems (e.g. VICON and MS-Kinect), 3D camcorders [275], and point cloud devices [274]. These technologies are applied in the construction industry to monitor workers [275–278], equipment and workers [279], and the physical progress of the project [280,281].

5.2.1.3 Automated systems and miscellaneous sensors

Within the construction industry's scope, automated control of tools, machines, and equipment can be used to verify their use. Furthermore, by inference determines the time and the volume of work performed by the worker through them. For example, rigging equipment has ohmmeters, and welding machines can be equipped with systems to control the amount of solder deposited.

Besides, it is possible to control the environmental factors at the on-site construction employing various sensors, in order to monitor the conditions of humidity, temperature, pressure, noise, luminance, and rainfall indices, among others. As automated systems and multiple sensors are already commercial products, few scientific studies apply these devices to assess workers' productivity.

For example, for the application of asphaltic concrete, a GPS positioning of the finishing equipment controlled the equipment path, and also, using temperature sensors and infrared images, the specifications of the applied material are evaluated [282,283]. The control of the compacting rollers is also diagnosed based on the equipment's path through GPS [284–288], and the rotation is identified using accelerometers [286,288]. Where the conditions of the materials in compaction are evaluated using temperature [287,288] and humidity [287] sensors.

5.2.1.4 Summary

Figure 5.1 presents the many sensors (embedded on devices/equipment/tags) to monitor construction sites activities. The hardware devices/equipment can bring embedded more than one sensor type (e.g. smartphones, smartwatches, cranes). Also, the workers themselves on-duty operating equipment/machine or handling tools/products are physical elements. For data communication, an essential physical infrastructure of different equipment types is needed to transmit, store, and process data (e.g. modems, gateways, bridge). The data can flow between devices/equipment’s, for example, through Wi-Fi or Bluetooth.

Finally, information connectivity will be mainly via Ethernet for IoT platforms on local or cloud data storage. Associated with the devices and equipment's are the native systems (embedded software) for their operation. Finally, different systems (interface software) are needed to store and process data such as operating systems and databases. Throughout the process of implementing the devices, their use, data collection and processing, various actors/knowledge is required.

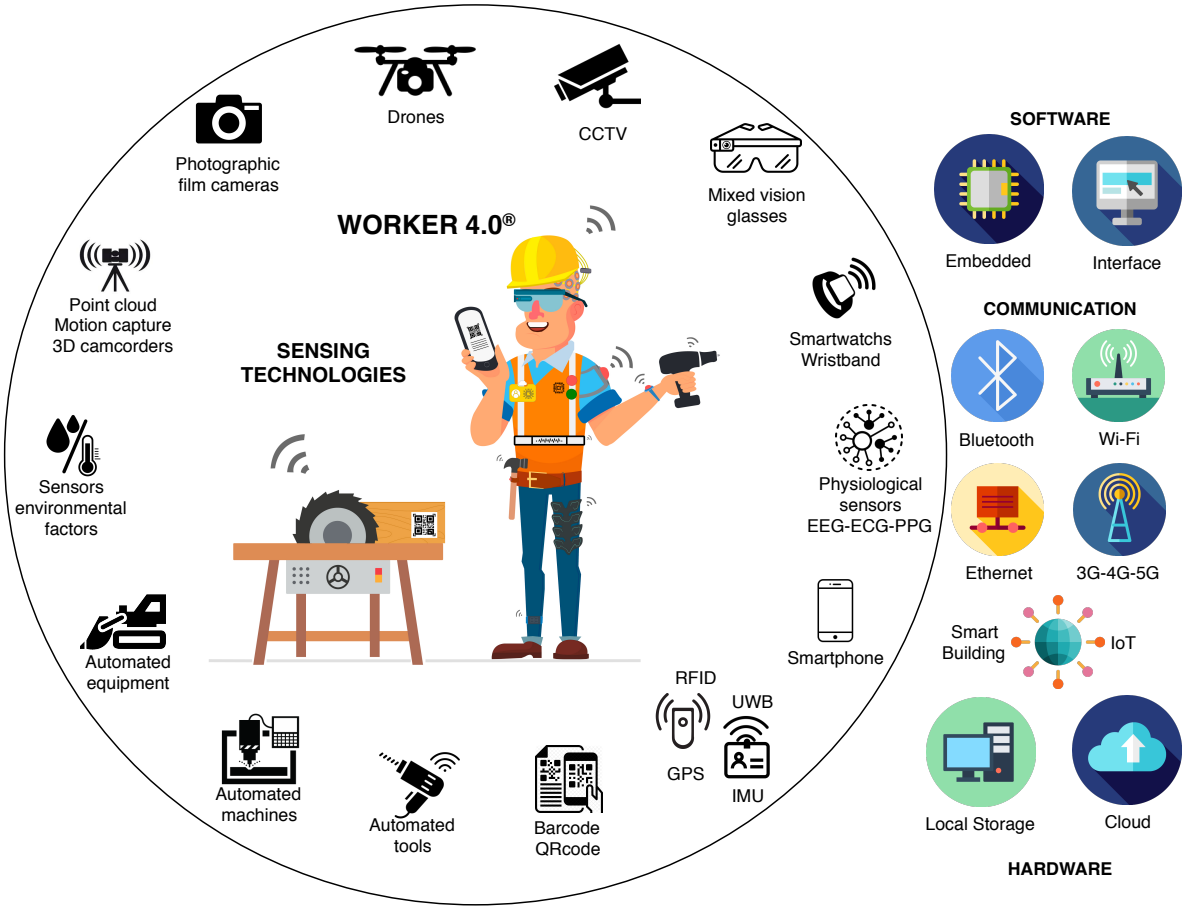


Figure 5.1 – Electronic devices.

When applying electronic devices to monitor tools and machines, it is necessary to look for small dimensions and lightness elements, since workers will handle these. The same principle is also relevant in monitoring materials and application elements, especially when monitoring the workers themselves. Also, considering that these elements are in significant numbers in construction environments, the low cost per monitored element positively potentiates the application of this type of technology.

It is worth mentioning that most of the technologies demand energy for their operation. In this way, it is sought, besides that this supply is already considered in the device's encapsulation, the not considerable increase of its volume, and that it has a proper autonomy to the use. However, when it is sought to monitor vehicles and equipment, there is no need to require miniature devices, and given the reduced number of devices, higher unit costs can be accepted. In all cases, the technology must have a

"no wires" concept, and it is desired that the device be contained in a single enclosure, and that does not require external elements such as wires and antennas.

Productivity monitoring in construction projects is highly complex, as it involves the evaluation of all elements (materials, tools, equipment, workers, etc.) over time, within a context of several interactive processes. With this, different approaches seek to determine and improve performance in segments of the vast production process.

For example, monitoring materials and application elements to assess the times they remain in storage, handling, and finally building are extremely relevant information given a Lean Construction concept. Moreover, locating and efficiently positioning these elements in real-time leads to directly positive results in on-site productivity and enables integrated management of the project schedule and quality and the computerization of the BIM (Building Information Modelling) model and obtaining a 4D view.

Most of the academic studies focus on identifying the areas of occupation and trajectories carried out by workers during their working day. Effective, based on their occupation are diagnosed the times elapsed within areas considered productive or non-productive.

Also, with the advent of small devices capable of measuring acceleration and velocity and the wearable technologies, and analysis of the workers' movements and gestures is possible. Within a concept of skeletonization, it can even diagnose direct work actions, such as sawing, hammering, painting, etc., allowing a detailed modelling of the production processes.

Undoubtedly, the environment influences the performance of the technologies. Construction projects can be predominantly carried out in open environments such as road works and land handling. As well as indoors sites such as building construction and underground services.

The construction industry segments also have peculiarities that produce significant impacts against electronic devices. For example, the heavy metal-mechanical construction has a significant concentration of pipes and metallic structures that negatively impact the base of the electromagnetic interference field. Table 5.1 shows the different technologies that can be used in the electronic productivity performance monitoring process based on the above-detailed. The type of application of the devices indicates the format of use of the technology in the monitoring. The type of technology identifies the primary technical resource of the harvesting system. Finally, it is indicated the monitoring possible in each electronic method of data collection.

Table 5.1 – Technologies in electronic devices and types of monitoring.

Application Type of Electronic Device	Type of Technology	Workers Monitoring Type					
		Location	Trajectory	Motions/ Gestures	Physiology	External Factors	Time/ Quantity
Portable or Wearable	RFID (Radio-Frequency IDentification)	x	x				
Portable or Wearable	UWB (Ultra-wide-band)	x	x	x			
Portable or Wearable	GPS (Global Positioning System)	x	x				
Portable or Wearable	IMU (Inertial Measurement Unit)	x	x	x	x		
Portable or Wearable	Smartphones	x	x	x	x		
Wearable	Electroencephalogram; Electrocardiogram; Photoplethysmography				x		
Wearable	Smartwatchs	x		x	x		
Wearable	Wristband			x	x		
Wearable	Athos (sportswear - muscular effort)			x	x		
Wearable	Motiv (ring - hands motion)			x	x		
Wearable	Nuada (glove - hands motion and power)			x	x		
Wearable	Mixed vision glasses (Google Glass, Microsoft HoloLens, etc.)	x	x		x	x	x
Images	2D images (CCTV systems, photographic and film cameras, etc.)	x	x	x		x	x
Images	2D images (drones - UAV, Unmanned Aerial Vehicle)	x	x	x		x	x
Images	3D images (point cloud, motion capture systems, 3D camcorders)	x	x	x			x
Automated Systems	Tools, Automated machines and equipment	x		x			x
Various Sensors	External sensors for measuring environmental factors (temperature, noise, etc.)				x	x	

Figure 5.2 presents the workers/environment conditions (features) that can be monitored by sensoring technologies at the Nano Level. This human data generated will allow the development of new methods to assess workers vital factors as skills, motivation and fatigue. Finally, that knowledge can be used to influence actions on workforce training to increase on-site safety and productivity.

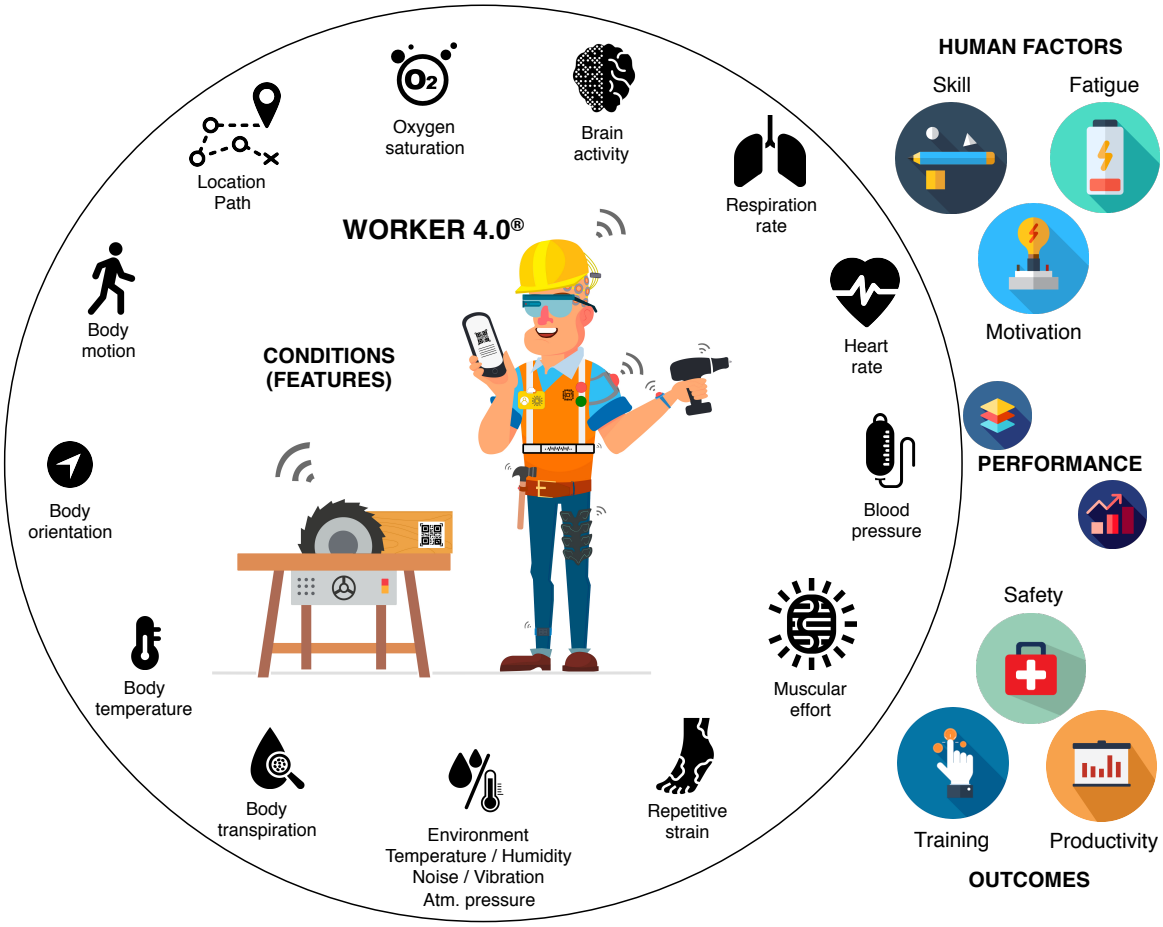


Figure 5.2 – Worker 4.0: Human data generated.

5.3 WORKFORCE ACTIVITIES CLASSIFICATION (SENSOR-BASED ACCELERATION)

For human activity classification, the hardware, sensor-based acceleration, must be embedded on the worker, through wearable sensing technologies. Most importantly, for construction sites/real-life applications, this hardware should be adequate to wear without interferences (e.g. wireless, weightless). Smartphones [98,289–292], wearables devices (e.g. IMU - Inertial Measurement Units [293–295] and Sports watch [200,296] have been applied as leading hardware for human activity classification. The hardware for activity classification comprises many components as accelerometers, magnetometer, gyroscope, Bluetooth, WI-FI, memory, battery, and might integrate GPS and sensors of light and temperature. The combination of sensors, e.g. accelerometers, magnetometer, gyroscope [295] increases the processing accuracy but at the same time, increases the hardware cost. The same dilemma is also placed in terms of the number of devices to cover the human body. A hardware solution based only on accelerometer will be more cost-efficient, and few devices offer a solution with

a lower cost. Table 5.2 presents conducted studies on craft workforce productivity focusing on sensors placement schema and monitored body movements.

Table 5.2 – Sensor-based studies conducted for activity classification.

Characteristic		No. of papers	References
Sensors	Accelerometer	4	[200,292,296–298]
	Accelerometer and gyroscope	5	[98,99,289,291,299]
	Accelerometer, gyroscope, and magnetometer	3	[290,294,295]
Movement of	Arm	5	[98,99,289,294,299]
	Arms and waist	2	[298,300]
	All Body	4	[290,292,295,297].
	Spine	2	[301,302]
	Wrist	2	[200,296]
	Wrist and leg	1	[291]

As shown in Table 5.3, it can be seen that the maximum number of activities analysed in a single study totals eight activities. It is also observed that a single experiment generated a series of publications. On average 6 to 7 individuals (subjects) perform the activities.

Table 5.3 – Studies on activity recognition.

Reference	Authors	Year	Subjects	Activity Recognition
[98]	Akhavian, Reza, and Amir Behzadan	2016	4	(1) Cutting Lumber; (2) Transportation; (3) Installation
[289]	Akhavian, Reza, Lianne Brito, and Amir Behzadan	2015	4	Category 1 [(1) sawing against (2) idling]; Category 2 [(3) hammering and (4) turning a wrench against idling]; Category 3 [(5) loading sections into a wheelbarrow, (6) pushing a loaded wheelbarrow, (7) dumping sections from a wheelbarrow, and (8) returning an empty wheelbarrow against idling]
[246]	Akhavian, Reza, and Amir H Behzadan	2016	4	(1) Cutting Lumber; (2) Transportation; (3) Installation

(*Continued*)

Table 5.3. Continued.

[99]	Akhavian, Reza, and Amir H Behzadan	2018	4	Category 1 [(1) sawing against (2) idling]; Category 2 [(3) hammering and (4) turning a wrench against idling]; Category 3 [(5) loading sections into a wheelbarrow, (6) pushing a loaded wheelbarrow, (7) dumping sections from a wheelbarrow, and (8) returning an empty wheelbarrow against idling]
[303]	Akhavian, Reza, and Amir H Behzadan	2016	4	Category 1 [(1) sawing against (2) idling]; Category 2 [(3) hammering and (4) turning a wrench against idling]; Category 3 [(5) loading sections into a wheelbarrow, (6) pushing a loaded wheelbarrow, (7) dumping sections from a wheelbarrow, and (8) returning an empty wheelbarrow against idling]
[291]	Zhang, Mingyuan, Shuo Chen, Xuefeng Zhao, and Zhen Yang	2018	9	(1) Standing, (2) Walking, (3) Squatting, (4) Cleaning up the template, (5) Fetching and placing rebar, (6) Locating the rebar, (7) Binding rebar, (8) Placing concrete pads
[294]	Tao, Wenjin, Ze Hao Lai, Ming C. Leu, and Zhaozheng Yin	2018	8	(1) grab tool/part, (2) hammer nail, (3) use power-screwdriver, (4) rest arm, (5) turn screw- driver, and (6) use wrench
[296]	Juhyeong Ryu, JoonOh Seo, Meiyin Liu, SangHyun Lee, and Carl T Haas	2016	5	(1) spread mortar, (2) bring and lay blocks, (3) adjust blocks, and (4) remove remaining mortar
[200]	Ryu, Juhyeong, Joonoh Seo, Houtan Jebelli, and Sanghyun Lee	2019	10	(1) spreading mortar; (2) bring and laying blocks; (3) adjusting blocks; and (4) removing remaining mortar
[300]	Joshua, Liju, and Koshy Varghese	2012	-	(1) Effective work, (2) Contributory work, and (3) Ineffective work
[298]	Joshua, Liju, and Koshy Varghese	2014	20	(1) Effective work, (2) Contributory work, and (3) Ineffective work
[304]	Joshua, Liju, and Koshy Varghese	2011	-	(1) fetch and spread mortar, (2) fetch and lay brick, and (3) fill joints

5.4 DATA PROCESSING

Various mathematical and statistical methods can be used in the processing and analysis of the data. In most cases, methods are used in conjunction with the example, the univariate and multivariate analyses [305] and, univariate analyses and Monte Carlo simulation [306]. Dynamic analysis methods and neural networks are also widely used.

However, it is a trend that applies AI, given the large amount of data collected by electronic devices and, in order to process such information quickly and autonomously. Academic studies focusing on the classification of human activities/actions develop algorithms based on Deep learning [204,294] and Machine-learning [200,297,307].

Machine and Deep learning are very similar autonomous and self-teaching system for training algorithms to find patterns/clusters and then use that knowledge to make predictions about new data [308]. Artificial intelligence has been evolving very fast, and new systems can improve the way data processing is made. For example, reinforced learning is, as well, an autonomous and self-teaching system that essentially learns by trial and error, not demanding training sets [308]. The domain of data processing is essential to accelerate the delivery of information based on EPM. As faster and more autonomous the data processing, more agile the delivery of solutions.

5.5 CHAPTER CRITICAL REVIEW

This chapter reviewed the concepts and techniques for assessing workers' performance through electronic devices and systems. The study conducted so far, which includes an analysis of productivity measurement models in CI to the challenges and barriers to implementing EPM (legislation, technologies, people, etc.), will support developing a framework to measure craft workforce productivity. The next chapter presents the conceptualisation of an approach to assess and modelling craft workforce productivity.

6
CRAFT WORKFORCE MOTION PRODUCTIVITY

6.1 INTRODUCTION

Firstly, this chapter reviews the concepts of work systems and motion studies to sustain the proposed innovation for Craft Workforce Motion Productivity. A conceptual approach to assess and modelling craft workforce productivity is delivered, connecting ways to collect data on-site electronically. Finally, it will introduce three key tools being: the Worker 4.0 Processes for Motion Productivity (9 processes); Worker 4.0 Flow to boost Productivity (Efficiency and Mechanization); Worker 4.0 Mapping chart (Two-hand methodology).

6.2 ELECTRONIC MOTION MONITORING

Since Frank and Lillian Gilbreth's research, work design and motion studies have been developed following different modelling/measuring productivity approaches, mainly through human observation of field activities [22,90,92]. The motion analysis [92], can be described as an in-depth study on tasks process. Nonetheless, current technological advances foster the automation of some manual data collection processes.

Likewise, these allow the development of new ways to measure the productive performance of Work Elements and Basic Motion Elements. As stated in the above chapters, new analysis processes focus on the geographical mapping of the location and workers trajectories in order to quantify the time spent in specific work areas [97,309]. Other studies seek a detailed analysis of workers' movements and gestures using the skeleton vectoring method [276,310]. Furthermore, the current technological development has strengthened the provision of wearable devices equipped with sensors to analyse the physiological aspects of individuals [202,248].

6.3 NANO LEVEL TO IMPROVE CI PRODUCTIVITY

As stated in Chapter 2, a possible spectrum of analysis to boost the CI's productivity is at the Nano Level. In order to provide a simple way to measure craft workforce productivity, the identification of each construction Work Element is adequate. Besides, Basic Motions Elements (e.g. walking and carrying) are very relevant for modelling tasks' process.

In order to find the route for the construction tasks' process transformation to improve productivity, the most important is to identify the "Work Method" [81] used by the craft workforce. This requires identifying the conversion technology (tasks) applied to those being made by workers' hands with or without the help of manual/electric tools or those tasks made with the support of some machine or equipment.

Finally, as stated before, the construction industry faces a productivity growth problem. Globally, between 1997 and 2017, CI labour productivity only grew 1% a year compared with 3.6% a year for the manufacturing industry [6]. Setting CI low productivity problematic into a cause/countermeasure matrix [311] makes it possible to identify the actual context and opportunities to solve it (Figure 6.1).

Figure 6.1.a plots the matrix where CI low productivity centred is split by four quarters. The zone where low productivity causes and countermeasures are both known is contained in the quarter (i), where the application of existing knowledge leads to low growth. Into quarter (iii) can be seen the zone where the low productivity causes are known, but the appropriate countermeasure is unknown. This is the fire-fighting zone (iii) [311], the knowledge available is not adequate to CI, and unproductive root causes are unknown, solutions end merely treating the symptoms. Where the cause is known, and countermeasure is not known, complex solutions are demanded (quarter ii). Into zone (ii) technology and process specialists are required [311] to lead to digitalisation opportunities applied to monitor the labour. The lack of specific tools to measure CI productivity misleads the problems root causes identification. The quarter (iv) shows the zone where the cause is not known, and countermeasure is known [311], where it is necessary to model the low productivity problem through iterative processes to understand the causes and to be able to take actions to improve the tasks processes.

The Worker 4.0 concept proposed in this work aims to indicate a path to increase CI productivity. As shown in Figure 6.1.b, a new sensored construction site focussing on monitoring the craft workforce employing a prone motion method can lead to clarifying the low productivity root causes. With the increase of low productivity causes/countermeasures knowledge, more straightforward solutions to the problems will allow a boost on CI productivity (Figure 6.1.c).

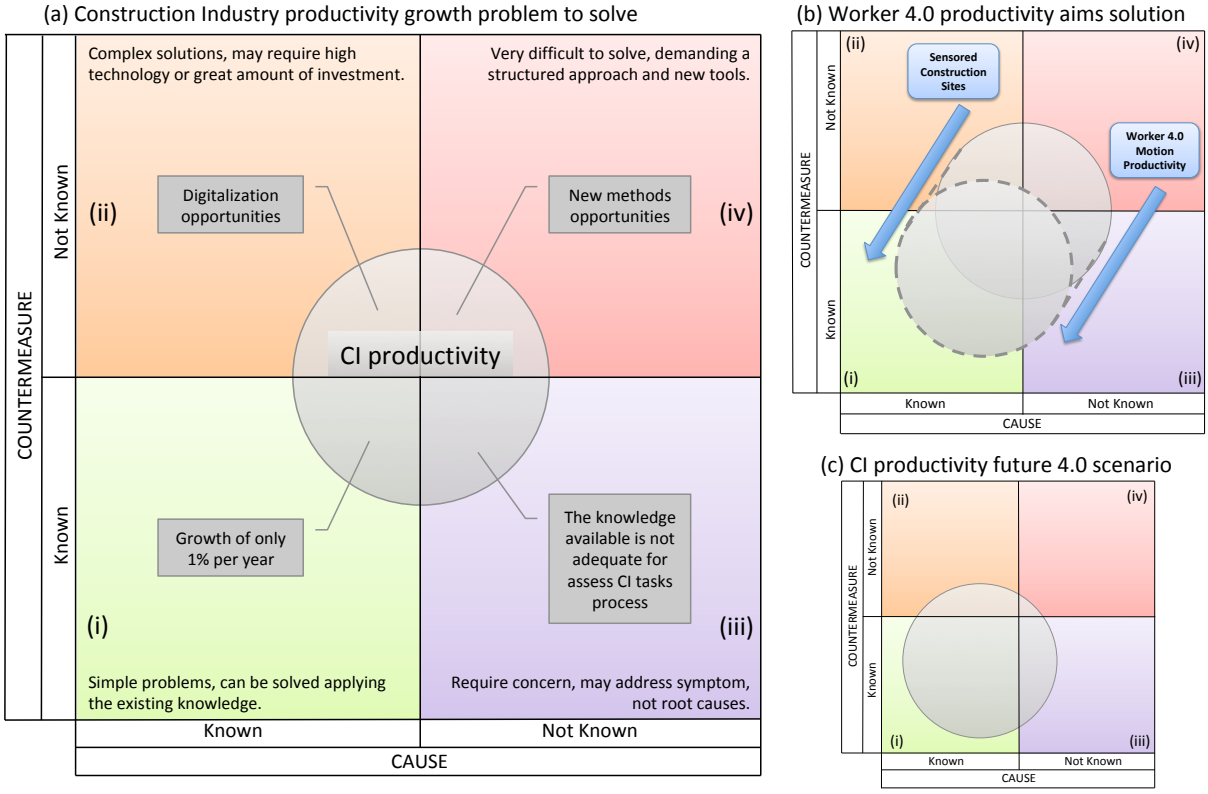


Figure 6.1 – Cause/Countermeasure matrix [311]: (a) Construction Industry productivity growth problem to solve; (b) Worker 4.0 productivity aims solution; (c) CI productivity future 4.0 scenario.

6.4 WORK SYSTEMS

Work systems consist of processes that utilize humans' physical and mental capabilities to deliver some work units (outputs) [92]. On-site construction tasks apply a converting technology (work method) to perform building elements (e.g. square meter of a wall) [81]. The workforce's productive states are connected to the activity classification, for example, productive or unproductive works.

The manufacturing industry has been applying motion study to save costs [160] and achieve a higher output rate [90]. The work cell method designing allows work automation scalability [160].

Rearranging the work processes sequence and introducing more automation and machines makes the jobs easier to be done and maximize efficiency [90,92,160]. Nevertheless, the two critical outputs of motion studies are workers less idle, and more process mechanization.

6.4.1 PROCESSES SYSTEMS AND PRODUCTIVITE STATES

Manual work systems (Figure 6.2.a) are often applied in the construction sector (e.g. laying bricks and painting with a brush) [92]. In this system, workers perform one or more tasks processes with their hands (supported by body structure) partly utilizing hand tools (without the use of power tools nor machines) [92].

It is also very current in the CI, the Worker-machine systems (Figure 6.2.b) which consist of a worker performing the tasks utilizing machines or electric/electronic tools, or operating some equipment (e.g. making a hole with a drill and digging with a backhoe) [92]. Often, the combination of manual and worker-machine work systems is performed to build a construction element (e.g. a wall, a roof, a path-way) [92].

Finally, it is not usually seen in the CI, the Automated systems (Figure 6.2.c), when a machine processes a work unit without demanding a worker direct effort [92]. The worker role in that system is to conduct a periodic evaluation of the work unit output process.

It can be inferred that the insertion of autonomous activities in construction work will give rise to the need for manual processes (e.g. the finishings and the connection elements) and worker-machine (e.g. supply of materials such as pumpable concrete).

One of the ways to classify the workforce is concerning the work that it performs, Adrian (2004), for example, indicates different attributions such as carpenter, mason or welder [91]. Another possible classification is the state that the worker is in a while carrying out a particular activity, and in this sense, there are two states: the Productive and the Nonproductive [91].

To a certain degree, the evaluation of the productive state depends on the observer's analysis, and according to Adrian (2004) the production state can be classified into three criteria [91], which are:

- Productive or direct work (e.g. handing a block, driving nails, welding);
- Contributory or support work (e.g. measuring an element, carrying products, carrying tools);
- Nonproduction work (e.g. standing idly, chatting, walking).

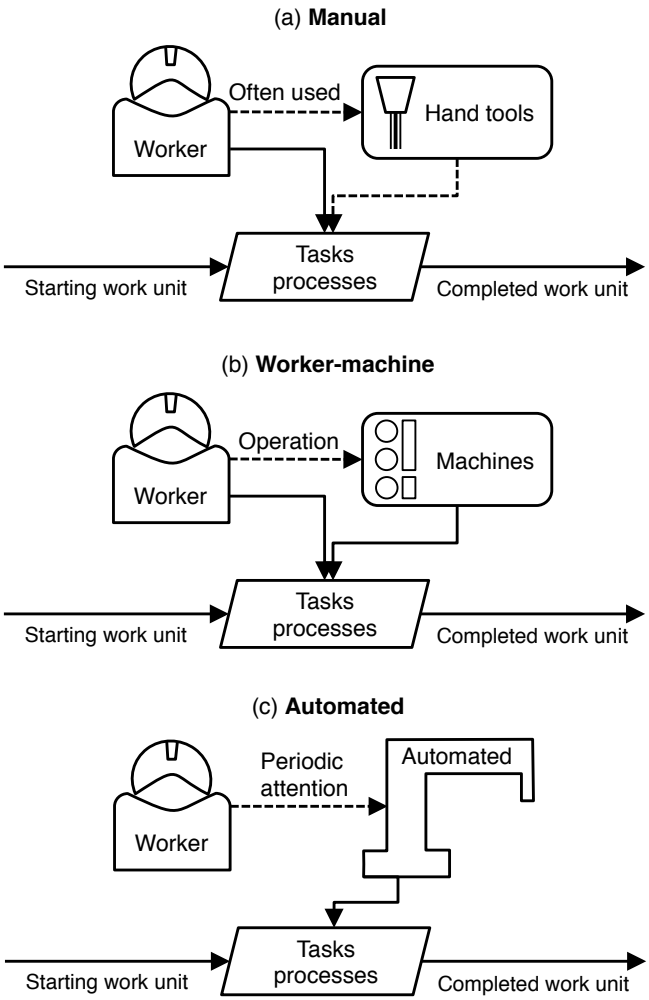


Figure 6.2 – Work systems: (a) Manual work system; (b) Worker-machine system; (c) Automated system. [92]

6.4.2 MICROMOTION STUDIES

Gilbreths established as part of motion analysis, a micromotion dimension with 17 basic motions (therbligs) that are present at all tasks, whether effective or ineffective work [22,90,92,160]. The principle of therblig is motions economy.

By identifying the motions that make up a task, it is possible to evaluate the activities that directly advance the work progress (effective therblig, Table 6.1, [90]). Motions that do not advance work progress (ineffective therblig, Table 6.2, [90]) should be eliminated or reduced to achieve better productivity. It should be noted that the study of motions based on therblig has a focus on reducing manual labour-effort by not evaluating the production cycle [160]. Also, micromotion studies are more effective on the assessment of works with highly repetitive operations or infrequent setup or maintenance procedures characteristics [160].

Table 6.1 – Effective Therbligs [90].

Directly advance progress of work. May be shortened but difficult to eliminate completely.		
Therblig	**Symbol**	**Description**
Reach	RE	Motion of empty hand to or from object; time depends on distance moved; usually preceded by Release and followed by Grasp.
Move	M	Movement of loaded hand; time depends on distance, weight, and type of move; usually preceded by Grasp and followed by Release or Position.
Grasp	G	Closing fingers around an object; begins as the fingers contact the object and ends when control has been gained; depends on type of grasp; usually preceded by Reach and followed by Move.
Release	RL	Relinquishing control of object, typically the shortest of the therbligs.
Preposition	PP	Positioning object in predetermined location for later use; usually occurs in conjunction with Move, as in orienting a pen for writing.
Use	U	Manipulating tool for intended use; easily detected, as it advances the progress of work.
Assemble	A	Bringing two mating parts together; usually proceded by Position or Move; followed by Release.
Disassemble	DA	Opposite of Assemble, separing mating parts; usually proceded by Grasp and followed by Move or Release.

Table 6.2 – Ineffective Therbligs [90].

Do not advance progress of work. Should be eliminated if possible.		
Therblig	**Symbol**	**Description**
Search	S	Eyes or hands groping for objects; begins as the eyes move in to locate an object
Select	SE	Choosing one item from several; usually follows Search.
Position	P	Orienting object during work, usually preceded by Move and followed by Release (as opposed to during for Preposition).
Inspect	I	Comparing object with standard, typically with sight, could also be with the other senses.
Plan	PL	Pausing to determine next action; usually detected as a hesitation proceding Motion.
Unavoidable Delay	UD	Beyond the operator's control due to the nature of the operation, e.g., left hand waiting while right hand completes a longer Reach.
Avoidable Delay	AD	Operator solely resposible for idle time, e.g., coughing.
Rest to Overcome Fatigue	R	Appears periodically, not every cycle, depends on the physical workload.
Hold	H	One hand supports object while other does useful work.

The assessment of micromotions operations can lead the development of different types of charts/flows include:

- Two-hand process chart (Worker right and left hands chart plotting their motions and delays) [90];
- Simo chart (Worker right and left arms chart plotting their motions and delays) [160];
- Operations analysis (Single worker performing serial activities) [160];
- Operator/machine (Worker and machine operation relationship) [160];
- Gang chart (Team of worker operation assessment) [160];
- Multimachine chart (Worker and several machines operation relationship) [160].

The micromotion studies allow assessing the performance of an individual, teams, and worker-machine activities [160]. The concept to improve the productivity of operations and processes are both based on analyzing a small group of tasks motions for:

- Eliminating unnecessary motions [160];
- Combining the work process to make tasks easier [160];
- Rearranging the actions sequence [160];
- Simplifying tasks avoiding idleness [160].

By reducing tasks time and effort the productivity will be positively impacted [90,92,160]. The analysis of machines' lead time and the synchronization of the processes that allow workers to increase their productive state actions will improve workers-machines efficiency [90,92,160].

Methodologies applying micromotion assessment may lead work/tasks processes redesign, such as the following tools:

- Motion economy principles (Designing and improving operations) [160];
- Motion pattern analysis (Evaluation of workstation effectiveness plotting finger motions) [160];
- Predetermined time standards systems (Time standards estimation by coded motion study) [160];
- Work station design (Workplace design based on motion and time study) [160].

6.4.3 MACROMOTION STUDIES

Also, the tasks can be studied by assessing process activity. As known, process flow literature has five classes of activities that are presented in all production tasks [90,92,160]. As characteristics symbols know them:

- Operation (Performing work dealing part of a product), symbolized by a circle [92,160];
- Inspection (Performing quality control work), symbolized by a square [92,160];
- Delay (Waiting time, do not advance work progress), symbolized by a big “D“[92,160];
- Transportation (Moving products), symbolized by an arrow [92,160];
- Storage (Used for long-range storage), symbolized by a triangle [92,160].

Most often, process studies aim to evaluate the activity flow of a product. The type of subject assessment conduct a different process chart classification [92]. Process macromotion studies may assess products, workers, equipment, information, forms, money, energy, or other assets/data amount time (chart format) or space (plan view format) [160].

As examples of process chart/flows are included:

- Process flow plan (A plan-view plant/site layout with activities overlaid) [160];
- Process operations chart (A serial/parallel sequence of operations) [160];
- Process chart (Preprinted form of all serial activities) [160];
- Flow process chart (Single format page contenting all serial/parallel activities) [160];
- Work cell load chart (A plan view contenting the repetitive operations) [160];
- Route sheet (Operations scheduling planner tool) [160];

Modelling the CI tasks processes can lead to a better evaluation of the on-site workflows, conducting projects to increase labour productivity.

6.5 WORKER 4.0 MOTION PRODUCTIVITY (W4MP)

This work proposes mixing Work Elements and Basic Motion Elements to enable the mapping process of all construction tasks, providing an adequate process to increase on-site production. The proposed production process modelling will allow the measurement of the amount of service performed by hand or mechanized in a similar method as recommended by Hwang et al. 2019 [33]. Likewise, assesses the unproductive and time spent in auxiliary activities.

Based on the background above, aiming to find a route to increase CI productivity, a method proposal called Worker 4.0 Motion Productivity (W4MP) is made. The work elements deliver essential information within the on-site construction tasks. The process analysis with a micro view at the basic motion elements using Therblig (Reach; Move; Grasp; Release; Preposition; Use; Assemble; Search; Select; Position; Inspect; Plan; Unavoidable Delay; Avoidable Delay; Rest to Overcome Fatigue; Hold) [90,102] is too much detailed and more relevant at an assemble industrial work stage design than to measure tasks performance on-site.

However, to provide a simple way to measure craft workforce productivity, identifying the construction work elements better detailing a macromotion operation level is adequate. Likewise, some of the basic motions as walking and carrying are also relevant to best understand the tasks' process in construction sites.

In order to find the route for the transformation of the process of the tasks to achieve improved productivity, the most important is to identify the work method of the tasks. It means to identify the conversion technology (tasks) applied, been these made by workers' hands with the help of manual tools, or with electric tools, also, that tasks made by machine or equipment.

The Nano Level is more prone to allow the increasing of the on-site productivity, a proposal for craft workforce motion productivity is presented. The craft workforce motion productivity framework, namely Worker 4.0 Motion Productivity (W4MP), establishes nine processes to map and measure performance. Therefore the nine processes are possible modelling any on-site building task, as presented in Table 6.3.

Table 6.3 – Worker 4.0 Processes.

Worker 4.0 Motion Productivity	**Group of movements and performance**	**Example**
Free-hand performing	One or both hands during the tasks, handling materials or products	putting a brick, etc.
Auxiliary tools	One or both hands during the tasks handling auxiliary tools	using a spirit-level, etc.
Manual tools	One or both hands during the tasks handling manual tools	using a trowel, etc.
Electric/Electronic tools	One or both hands during the tasks, handling electric/electronic tools	using a drill, etc.
Machines operation	One or both hands during the tasks, dealing with machines/workstations or dealing with equipment	using a bench circular saw, using a backhoe, etc.
Robotic automation	Automated work based on robotic equipment	robotic bricklaying arm, etc.
Do not operating value	Doing any productive work. That does not advance the progress of the tasks. Also identified as "ineffective Therbligs" or "not productive"	planning, searching, chatting, resting, human needs, etc.
Walking	Walking without carrying anything on hands	going to the WC, idleness, etc.
Carrying	Walking carrying something on hands	products, equipment, tools, etc.

Table 6.4 presents the nine processes of craft workforce motion productivity and their acronyms detailing the:

- The Element level of the tasks (Work Element or Basic Motion Element) [92,102] and autonomous when Robotic automation;
- Processes characteristic (Operation, Inspection, Delay, Transportation/Storage), processes meanings and symbols follow the same pattern of well-known Process Chart Flow applied in macromotion studies [160];
- Productive state (Productive or Direct work, Contributory or Support work, Nonproduction work) the productive state addresses the workforce performance during the development of tasks [91], and Autonomous Production in the case of automated robotic equipment;
- Electronic Monitoring (Acceleration, Position, Sound/Noise), suggests an approach to monitor the performance employing electronic devices. Those three elements are considered the minor features to control and to measure the performance.

Electronic monitoring more aspects than the ones indicated would provide more outputs, but as well, it would increase complexity and cost. It is possible to interpreter the activity being performed based on

the hands and the legs motions when accomplishing all nine processes. At the same time, some of then (Free-hand performing; Auxiliary tools; Manual tools; Electric/Electronic tools) can be captured just by the hands' motion. The legs contribute to that assessment and provide more useful information for others (for example, Do not operating value; Walking; Carrying).

Therefore, it is considered appropriate to wear devices on wrists or arms and legs to, at least, capture that motion acceleration. Beyond, the monitoring of workers' body rotation and location, if added, can increase the analysis.

As an example, it can make it possible to interpret the collection/carrying of elements from storage areas or machine/equipment movement from monitoring the trajectory. Furthermore, Sound/Noise tracking of electric tools, machines and equipment can allow the identification of operating times and indicate the components-specific type. Besides, it sets an everyday basis for the measurement of the energy expended (e.g. kcal/min, Btu/min) on each process.

Table 6.4 – Worker 4.0 Processes: specifications and patterns.

Worker4.0 Motion Productivity	**Acronym**	**Element level of the Tasks**	**Process**		**Productive state**	**Monitoring**
			Indication	**Symbol**		
Free-hand performing	FHP	Work Element	Operation	○	Productive or Direct work	Acc.
Auxiliary tools	AUT	Work Element	Inspection	□	Contributory or Support work	Acc.
Manual tools	MNT	Work Element	Operation	○	Productive or Direct work	Acc.
Electric/ Electronic tools	EET	Work Element	Operation	○	Productive or Direct work	Acc. + So.
Machines operation	MOP	Work Element	Operation	○	Productive or Direct work	Acc. + Loc. + So.
Robotic automation	RBA	Autonomous	Operation	○	Autonomous Production	Acc. + Loc. + So.
Do not operating value	IDL	Basic Motion Element	Delay	D	Nonproduction work	Acc. + Loc.
Walking	WLK	Basic Motion Element	Delay	D	Nonproduction work	Acc. + Loc.
Carrying	CAR	Basic Motion Element	Transportation/ Storage	Δ➔	Contributory or Support work	Acc. + Loc.

Note: Acc. = Acceleration; Loc. = Location (x;y;z); So. = Sound detector

Figure 6.3 graphically presents how the W4MP nine processes are interrelated with all layers of classification. It is possible to abstract that when modelling processes with the classification of workers' actions, it will be possible to visualize how time/effort is spent. For example, how long the team has been operating or is nonproductive and how impacts as long distances within the construction site can decrease production performance.

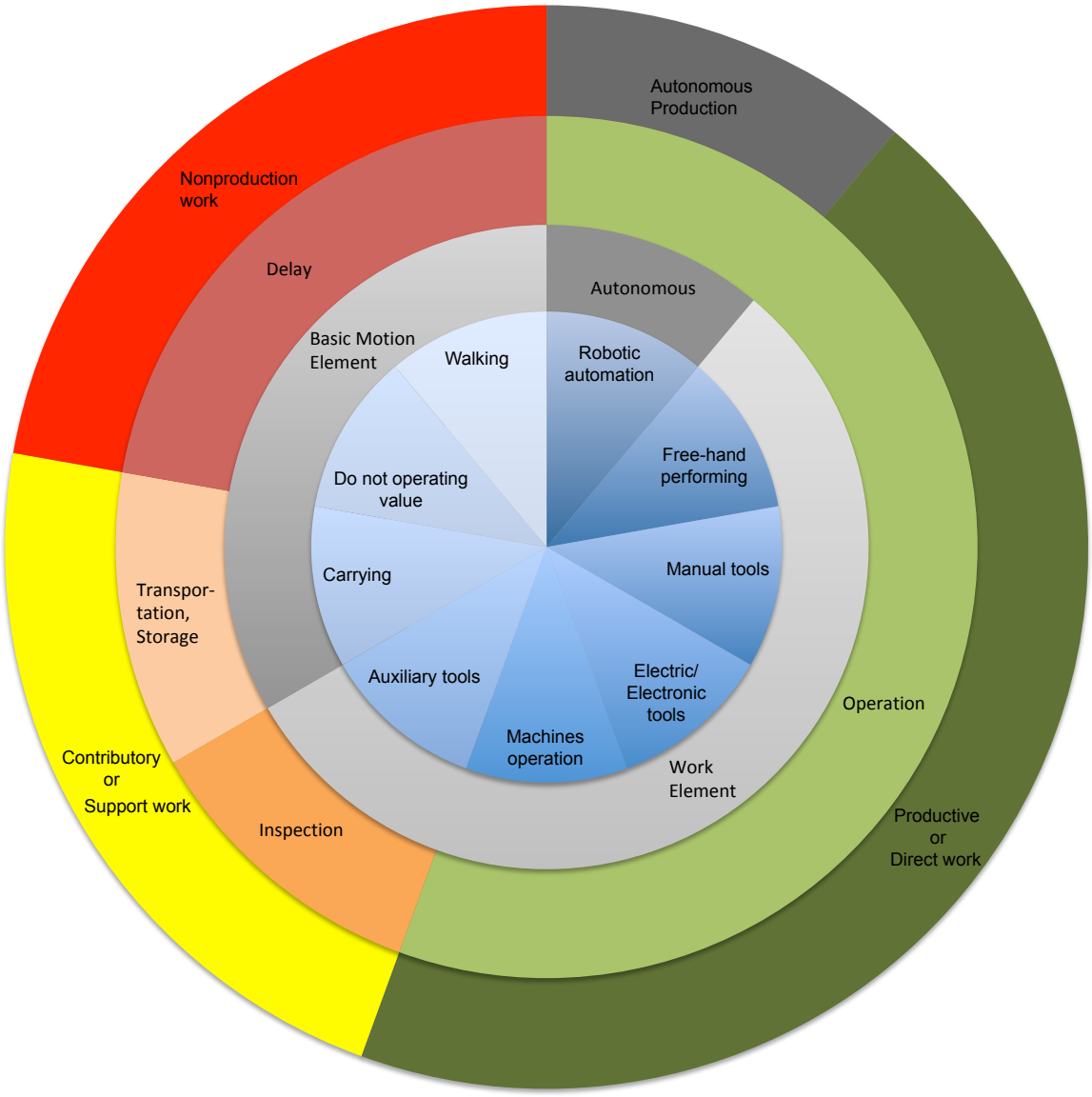


Figure 6.3 – W4MP and layers of classification.

6.6 MOTION PRODUCTIVITY PROCESS TO BOOST EFFICIENCY AND MECHANIZATION LEVELS

Figure 6.4 presents a flowchart of processes or the Worker 4.0 Motion Productivity to boost productivity framework. Based on the following assumptions and the designed flow, Table 6.5 presents the first analysis indications on how to boost efficiency and mechanization levels.

Assumptions

- All construction activities have a mix of operations performed only with the hands and others with the aid of tools (either manual or auxiliary or electrical) or machines or equipment;
- The handwork component (with one or both hands) is intrinsic/inherent to construction activities;
- Operating times should be maximized;
- Automated and Mechanical performances are higher than manual performance;
- Processes performed with tools have higher performance than the manual ones (not using tools);
- To achieve improved productivity, the tasks processes should be mechanized or automated;
- Inspections and verifications performed by the workers themselves should be reduced;
- Easily assembled templates and elements that require no measurement are prone to accelerate processes.

Table 6.5 – Worker 4.0 Motion Productivity: efficiency and mechanization analysis.

Worker 4.0 Motion Productivity	**First analysis indications on how to boost efficiency and mechanization levels**
Free-hand performing	Does the activity justify the use of any tool, mechanized or automated robotic equipment?
Auxiliary tools	Can it be eliminated? Can it be used as an electric/electronic tool?
Manual tools	Does the activity justify the use of an electric/electronic tool or mechanized or automated robotic equipment?
Electric/Electronic tools	Does the activity justify mechanized or automated robotic equipment?
Machines operation	Does the activity justify automated robotic equipment?
Robotic automation	If that robotic solution demands for workforce auxiliary work, can it be avoided or shortened?
Do not operating value	Can it be avoided or shortened?
Walking	Can it be avoided or shortened? Can the worker carry something?
Carrying	Can it be avoided or shortened? Does the activity justify automated equipment?

The flow presented in Figure 6.4 is oriented to increase automation and mechanization in the process of construction tasks. Therefore, for the operatives process, this flow indicates the path of the most extreme change, that is, automation. Of course, the decision to automate the production process goes through an analysis of technical-economic opportunity/feasibility. With this, the options for changes guide in the direction of mechanization, use of electric/electronic tools and even the option for hand tools given the processes carried out only with the hands.

As for auxiliary works carried out with the use of hand tools (e.g. plumb, level, measuring tape) it is indicated first to use elements that do not contain controls/gauges, thus eliminating this need, such as elements with a fitting system. Indeed, since it is not possible to eliminate these measurements, it is preferable to use electronic means to speed up the process. Nevertheless, mechanized systems can/should self-assess their quality and compliance.

Finally, it is relevant to seek to eliminate the idlest activities: not operating on value, walking, or carrying. If this is not possible, it is necessary to shorten these times/actions to provide an increase in the processes that add value to the products of the tasks.

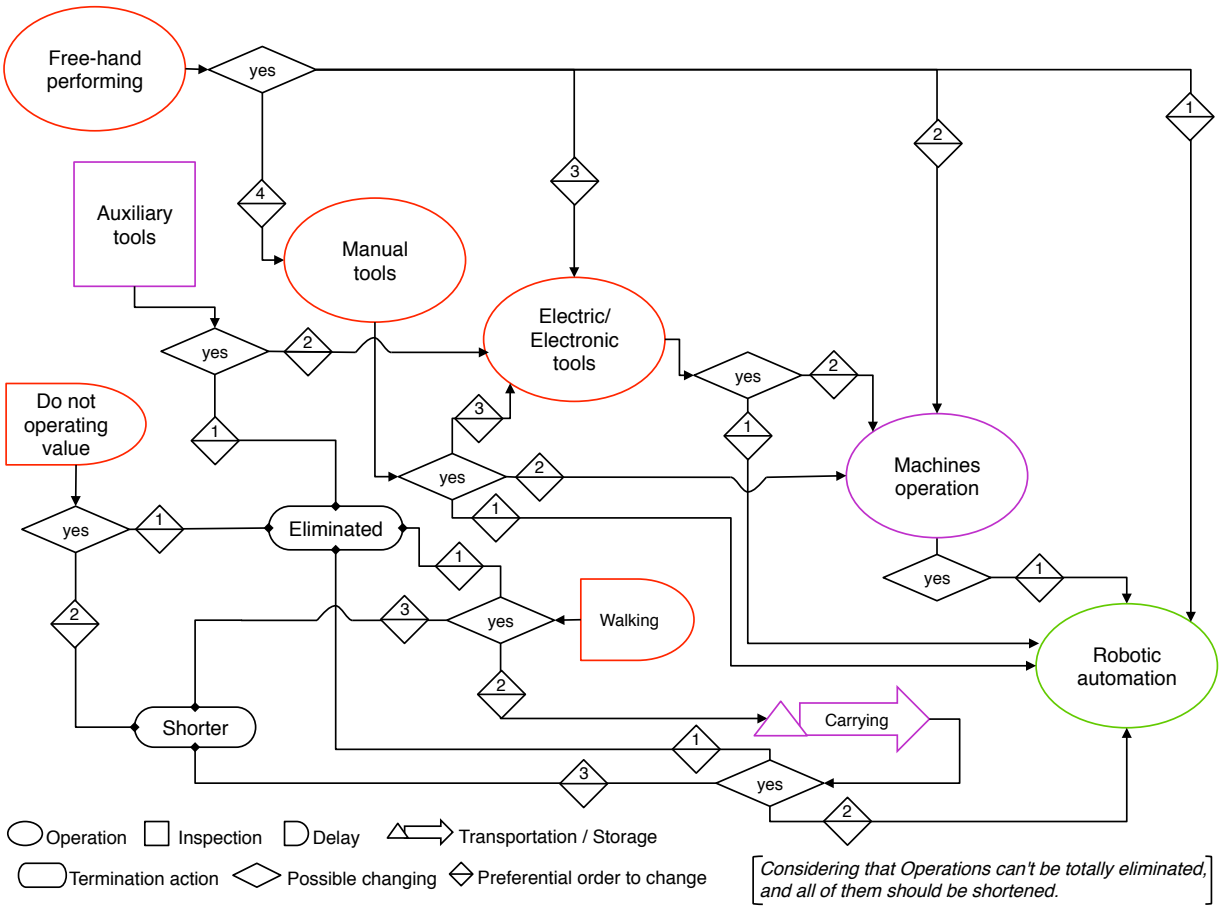


Figure 6.4 – Worker 4.0 Flow to boost Productivity.

According to Hwang *et al.* (2019), there is a lack of academic research on the assessment of mechanization in building construction projects [33]. Hwang *et al.* (2019) proposed a mechanization index assessment tool for projects based on a detailed analysis of the tools and measuring the level value regarding a qualitative survey [33].

It is undoubtedly vital to measure the level of mechanization of construction tasks. Much is said that CI is handmade with little use of machinery and equipment; however, little is measured and known. In addition to measurement, it is crucial to understand how mechanized work is inserted in production processes. Simple mechanization does not guarantee high performance; the productive context of the crew enhances this. For example, it is relevant to know how many crew members will support the work of a machine. Besides, whether workers can carry out activities in parallel or whether they should wait for the mechanical process are critical elements in the productive context. However, the proposed concept of measuring the mechanization level is derived primarily from a useful measurement in the field, considering all the processes of the crew involved.

Based on the Worker 4.0 Motion Productivity (W4MP), it is pretended to quantitative measure the mechanization of the tasks conducted by the craft workforce. Equation (1) presents the W4MP Mechanization index. The concept measures the proportion of the three mechanized processes (EET - Electric/Electronic tools; MOP - Machines operation; RBA - Robotic automation) upon the Operation processes, without considering the other processes as Inspection, Delay, and Transportation/storage. The analysis of these results based on the status quo of building construction tasks a classification scale is proposed, as following:

- Low - 0% to 20%;
- Moderate - 21% to 40%;
- High - 41% to 60%;
- Very high - above 61%.

$$(M4MP)\ Mechanization\ index\ = \frac{EET+MOP+RBA}{\sum Operation\ Processes} \qquad (1)$$

Where:

EET = Electric/Electronic tools;

MOP = Machines operation;

RBA = Robotic automation;

Operation Process = (FHP + MNT + EET + MOP + RBA);

FHP = Free-hand performing;

MNT = Manual tools.

It is based on the qualitative analysis of the responses regarding the efficiency of the processes and the quantitative values of each process and the mechanization index that the W4MP method will allow ways to improve productivity in the on-site construction projects.

6.7 WORKER 4.0 MODELLING CHART

Both hands' monitoring can allow the formation of a left-hand/right-hand chart (very applied in assembly process modelling [90,92,160]) where each hand instant motion is classified as a known process (e.g. therblig) and is plotted into two timeline columns [90,92,160]. The concept of this chart is evaluating the workers' operation to eliminate one-hand operation [90,92,160]. It is known that it is impossible to use both hands for the entire working time [90,92,160]. However, it is observed that the manufacturing industry has improved its operations using this method for workstations evaluation [90,92,160].

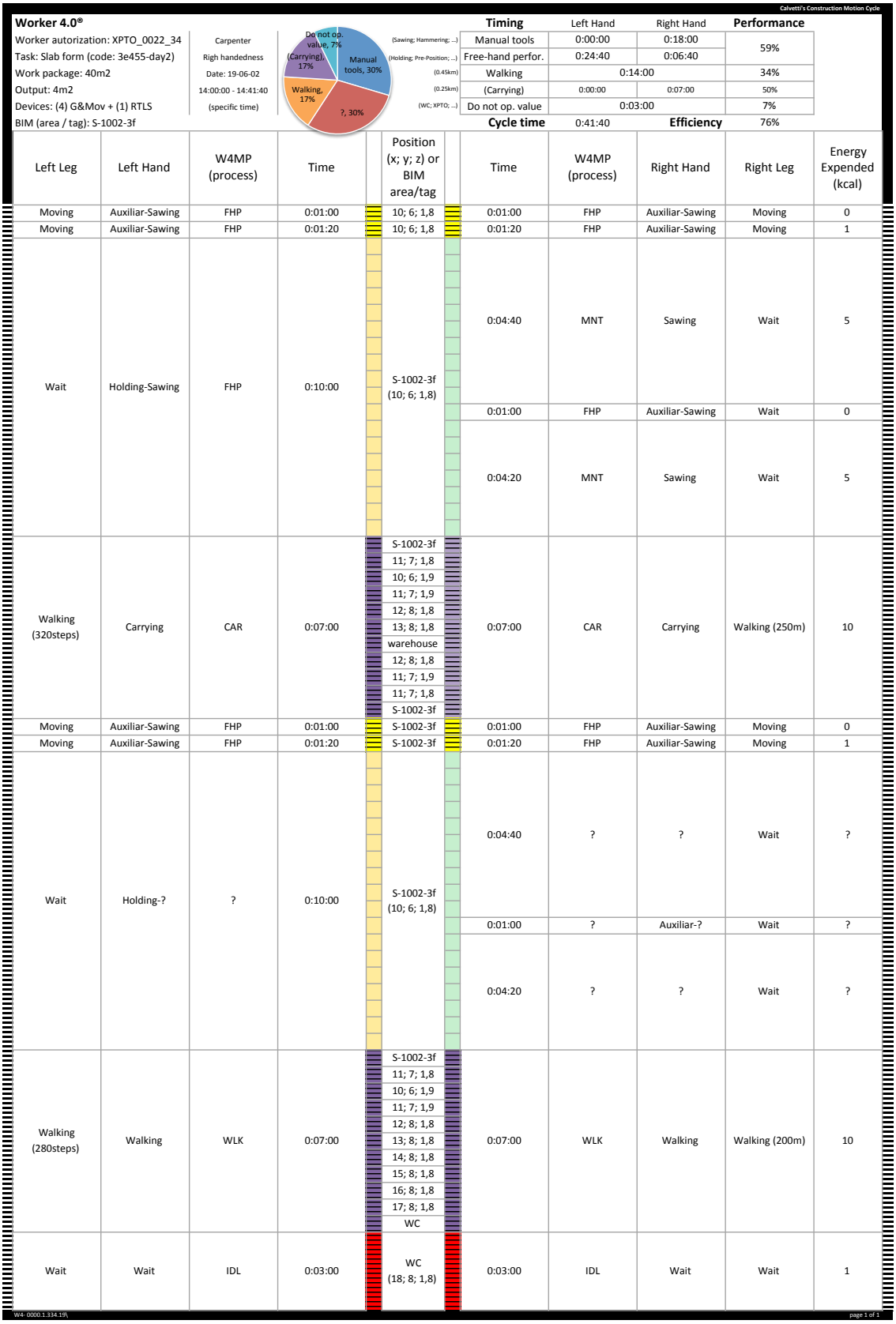
The Worker 4.0 Modelling Chart was designed based on that two-handed chart (see Figure 6.5). This chart consolidates all the concepts above presented. The top left (first and second columns) presents the information about the task and the worker (e.g. work package, output quantity, worker profession, day and time). A chart evidences that the proportionality of the processes labelled could be seen at the middle top. Finally, at the top right, a summary timing based on the Worker 4.0 motion productivity processes are presented where the cycle time and the performance efficiency can be determinate.

In the Chart sequence, appear twelve informative columns, where at the centre can be seen one column with the information of geo-position (x; y; z) or a BIM Space/tag identification, side by side it presents two columns with graduation (time) and colours (the type of process). Next, this centred column from left (four columns) and right (four columns) presents the respective pieces of information about workers hands and legs. Where on leg and hand information it may show a detailed classification of the activity (e.g. holding, sawing, walking).

Also, for each labelled hand/leg, the detailed information has time duration measured and a Worker 4.0 Motion Productivity (W4MP) classification describing the activity. Finally, a column in the right presents the workers estimated amount of calories expended. If it is not an already known activity, it will appear as (?), when the analyst identifies that task (e.g. hammering) the processing system method (e.g. machine learning) understands it and records for labelling. Forward, this gap is filled as labelled (e.g. hammering). The system in the next similar activities ones "registers" the pattern of the new action identified.

Worker 4.0 Modelling Chart is enabling modelling of production processes for a detailed analysis of productivity. It is possible to evaluate in time (hours, minutes, and even seconds) the workers' motions captured by the sensing wearables technology (in the case hands and legs). Still, it is possible to increase the analysis and the algorithms based on geolocation and tools' noise.

The processing of data through artificial intelligence will allow the automation of the labelling of activities. In this way, a future system can be organically supplied, only giving rise to small calibrations and adjustments. This chart can provide a streamlined view on productivity that can be used for multiple purposes such as training, by comparing an optimal performance with each worker results.



Calvetti's Construction Motion Cycle

Worker 4.0®

Worker autorization: XPTO_0022_34
Task: Slab form (code: 3e455-day2)
Work package: 40m2
Output: 4m2
Devices: (4) G&Mov + (1) RTLS
BIM (area / tag): S-1002-3f

Carpenter
Righ handedness
Date: 19-06-02
14:00:00 - 14:41:40
(specific time)

Timing	Left Hand	Right Hand	Performance
(Sawing; Hammering; ...) Manual tools	0:00:00	0:18:00	59%
(Holding; Pre-Position; ...) Free-hand perfor.	0:24:40	0:06:40	
(0.45km) Walking	0:14:00		34%
(0.25km) (Carrying)	0:00:00	0:07:00	50%
(WC; XPTO; ...) Do not op. value	0:03:00		7%
Cycle time	0:41:40	**Efficiency**	76%

Left Leg	Left Hand	W4MP (process)	Time	Position (x; y; z) or BIM area/tag	Time	W4MP (process)	Right Hand	Right Leg	Energy Expended (kcal)
Moving	Auxiliar-Sawing	FHP	0:01:00	10; 6; 1,8	0:01:00	FHP	Auxiliar-Sawing	Moving	0
Moving	Auxiliar-Sawing	FHP	0:01:20	10; 6; 1,8	0:01:20	FHP	Auxiliar-Sawing	Moving	1
Wait	Holding-Sawing	FHP	0:10:00	S-1002-3f (10; 6; 1,8)	0:04:40	MNT	Sawing	Wait	5
					0:01:00	FHP	Auxiliar-Sawing	Wait	0
					0:04:20	MNT	Sawing	Wait	5
Walking (320steps)	Carrying	CAR	0:07:00	S-1002-3f 11; 7; 1,8 10; 6; 1,9 11; 7; 1,9 12; 8; 1,8 13; 8; 1,8 warehouse 12; 8; 1,8 11; 7; 1,9 11; 7; 1,8 S-1002-3f	0:07:00	CAR	Carrying	Walking (250m)	10
Moving	Auxiliar-Sawing	FHP	0:01:00	S-1002-3f	0:01:00	FHP	Auxiliar-Sawing	Moving	0
Moving	Auxiliar-Sawing	FHP	0:01:20	S-1002-3f	0:01:20	FHP	Auxiliar-Sawing	Moving	1
Wait	Holding-?	?	0:10:00	S-1002-3f (10; 6; 1,8)	0:04:40	?	?	Wait	?
					0:01:00	?	Auxiliar-?	Wait	?
					0:04:20	?	?	Wait	?
Walking (280steps)	Walking	WLK	0:07:00	S-1002-3f 11; 7; 1,8 10; 6; 1,9 11; 7; 1,9 12; 8; 1,8 13; 8; 1,8 14; 8; 1,8 15; 8; 1,8 16; 8; 1,8 17; 8; 1,8 WC	0:07:00	WLK	Walking	Walking (200m)	10
Wait	Wait	IDL	0:03:00	WC (18; 8; 1,8)	0:03:00	IDL	Wait	Wait	1

W4- 0000.1.334.19\

page 1 of 1

Figure 6.5 – Worker 4.0 Motion Productivity: Flow to boost productivity.

6.8 CHAPTER CRITICAL REVIEW

In this chapter, a framework was developed to measure and model the productivity of CI craft workers. The use of electronic devices for data collection is enhanced. The model presented seeks to evaluate the process of CI tasks. This analysis ensures the understanding of local productivity factors and enhances production, generating opportunities for actions to mechanize tasks. Based on the reviewed literature and the proposals made, application cases are presented in the next chapter that seeks to test and validate such new concepts.

7
TESTING EPM AND VALIDATION OF THE PROPOSED FRAMEWORK

7.1 INTRODUCTION

This chapter presents a series of practical applications to test and validate the proposed framework. Construction tasks circuit activities were designed to test and postulate the electronic collection and data processing. Furthermore, on-site experiments sampling construction activities and fulfil the processes modelling proposed. Finally, craft workers are introduced to electronic performance monitoring by wearing devices, and they delivered feedback about it.

7.2 EPM LABORATORY EXPERIMENT SIMULATING CONSTRUCTION TASKS

Experiments were carried out in the CONSTRUCT/Gequaltec (University of Porto Faculty of Engineering) laboratory to test the feasibility of using accelerometers to collect data and recognize/classify construction workers' activities. In an indoor circuit, ten different activities were performed: FHP - Freehand performing activity (one); MNT - Manual tools processes (five); IDL - Do not operating value (three); WLK - Walking (one).

7.2.1 METHOD

As shown in Figure 7.1, after completing the circuit containing ten construction activities, each simulation had its actions labelled every second. To then be processed and evaluated by two different methods. To summarise the analysis, a graphical analysis of the accelerations collected during each activity's performance was made. Finally, a qualitative analysis of the two methods was provided.

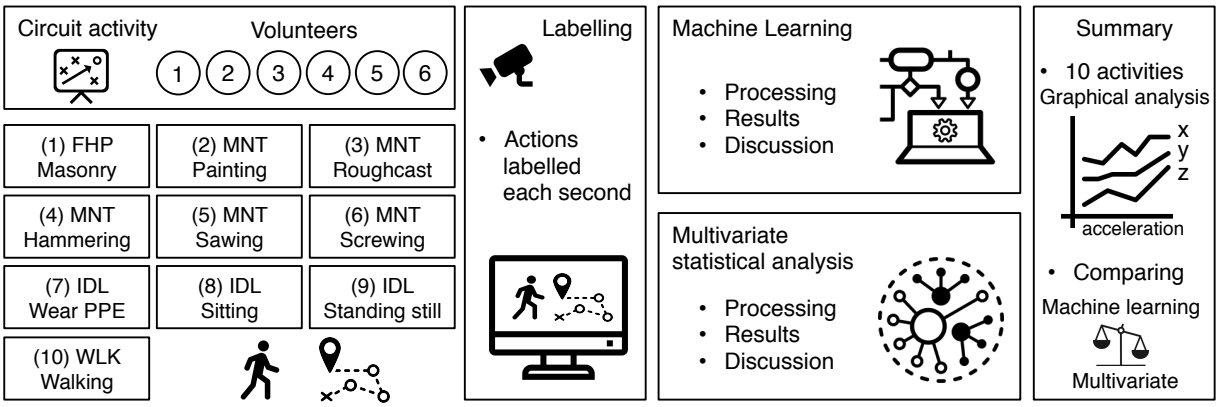


Figure 7.1 – Laboratory experiment method.

7.2.2 DATA COLLECTION

For an efficient construction craft workforce performance monitoring, it is essential the assessment of at least the hand-tasks the walking-travelling and the idleness. A total of six volunteers were equipped with three devices, two on both wrists and one on the dominant leg's ankle. IMU - Inertial Measurement Units (format similar to watches) devices were used and collected 3-axis data in a sampling frequency of 100 Hz with a 1-second epoch output, Figure 7.2. Each data point is thus represented as a vector containing the timestamp of the reading and nine acceleration values (one for each axis of the three accelerometers).



Figure 7.2 – Wearables to collect accelerations.

The data was labelled manually using a synchronised video recording of the circuit. The data points of each activity were: Painting (1562); Sawing (1466); Hammering (1419); Walking (1411); Masonry (863); Screwing (759); Sitting (624); Roughcasting (621); Standing still (296); Wearing (PPE) Personal Protective Equipment (287).

Following, those activities were clustered into three small balanced groups based on the characteristics. First, it was established a mixed group with the only process of “Free-hand performing” activity (Masonry) plus two “Manual tools” processes (Painting and Roughcasting). A

second, just containing “Manual tools” (Hammering, Sawing and Screwing). Moreover, a third composed by “Do not operating value” (Wearing PPE; Sitting; Standing still) and “Walking” (Walking).

7.2.2.1 Circuit-activity

A concept of the circuit was established, taking into account two main factors: (1) simulate an interactive work scenario seen in the on-site construction projects. Moreover, (2) avoid a binary analysis, where only one action would be evaluated in the face of the stopped state. It is possible to identify in some studies, such a binary approach [299], which first does not occur in practice, and second, it is easy to analyse and process (does not indicate significant results).

For this reason, basic daily activities were selected, which are part of the daily life of workers of different functions. It can be inferred that, given the role of a specific worker, his actions can be previously mapped, which would facilitate the classification of his activities. Also, according to Adrian (2004), at least 50% of the workforce time on-site is spent on non-productive activities (e.g. walking, drinking water, talking to co-workers) [91].

Also, the formation of the three groups of analysis with different processes and their respective activities were based on diversification. With this, it was a pursuit to evaluate the variability in the classification accuracy's performance through the different groups of activities with different motions patterns.

However, in the group "Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)", it has a mix with a free hand motion activity (masonry) and two others with static action with a predominance of high-frequency of the predominant hand motions and only a few motions of the non-dominant hand supporting the actions.

In the group "Manual tools (Hammering, Sawing and Screwing)", there is the uniqueness of actions with hand tools also with non-movement characteristics of the legs with a predominance of a high frequency of the predominant hand motions and only motions support on the non-dominant hand.

Finally, on grouping "Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking)" it mixes the walking movement to actions of resting and also some unusual movement activities such as the wearing of protective equipment (e.g. gloves, glasses, helmet).

The activities were spread through different activity stations, as seen in Figure 7.3. Figure 7.4 displays the circuit run path. In summary, the subject (volunteer) starts the circuit by standing still for a few seconds, followed by a gearing up phase, in which protective gloves, glasses, helmet and jacket are equipped. Afterwards, the subject collects two bricks from Station 2, lays them in Station 7, and repeats this action – this constitutes the masonry task. Each remaining productive task (sawing, hammering, screwing, painting, roughcasting) is successively intercalated with the masonry task until a total of 20 bricks have been laid in a brick wall. Finally, the subject removes the equipment, sits in Station 9, and after a few seconds stands still in the end area of the circuit, thus finishing it. In order to introduce some randomness in the circuit, subjects could transfer 2 or 4 bricks at a time between masonry stations. Furthermore, both brushes and rolls were available for painting. Subjects could also either remain idle while sitting or drink water and eat snacks that were available in Station 9. [312]

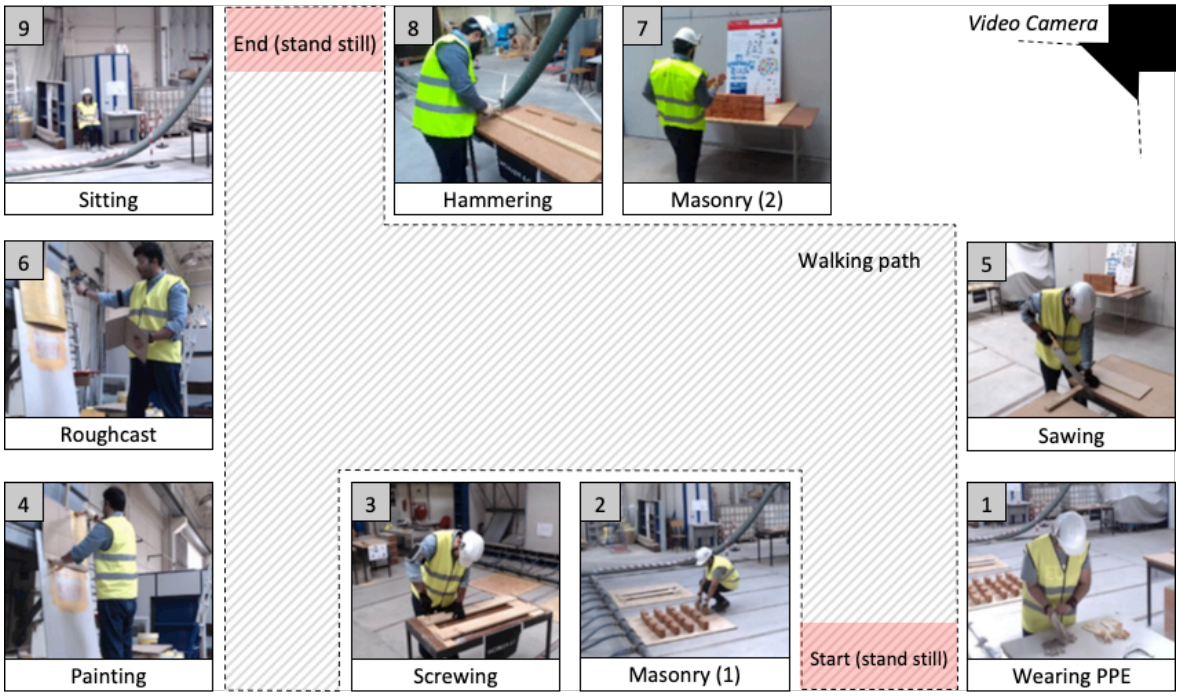


Figure 7.3 – Volunteers performing activities. [312]

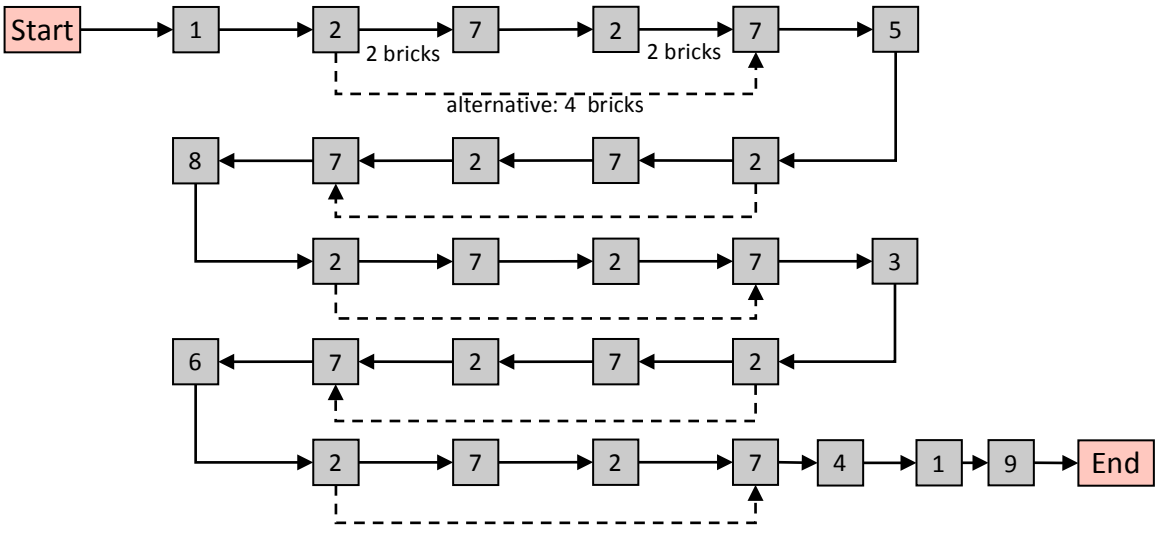


Figure 7.4 – Circuit run path. [312]

7.2.2.2 Sample

A total of six subjects performed the activity-circuit. The subjects initially answered a survey indicating their respective gender, age, height, weight, and experience in each of the productive

activities to be conducted [312]. This information can be seen in Table 7.1 [312]. Afterwards, each subject performed the circuit three times, averaging around 8.6 minutes per run [312]. In total, 9308 seconds (data points) were acquired. The data distribution per subject and activity can be seen in Figures 7.5 and 7.6 [312].

Table 7.1 – Subject characteristics. [312]

Subject	Gender	Age (years)	Height (cm)	Weight (kg)	Has experience with the analysed productive tasks?					
					Hammering	Masonry	Painting	Roughcast	Sawing	Screwing
1	Male	41	176	88	Yes	Yes	Yes	Yes	Yes	Yes
2	Female	28	155	58	Yes	Yes	Yes	Yes	Yes	Yes
3	Female	25	155	48	Yes	Yes	Yes	No	No	Yes
4	Female	30	148	44	Yes	Yes	Yes	No	Yes	Yes
5	Female	33	158	47	Yes	Yes	Yes	Yes	Yes	Yes
6	Male	35	172	74	Yes	Yes	Yes	No	Yes	Yes
	Average	32	161	60						
	Median	32	157	53						

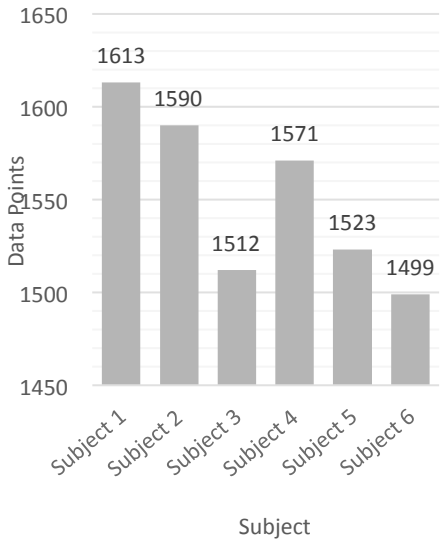


Figure 7.5 – Subjects data points. [312]

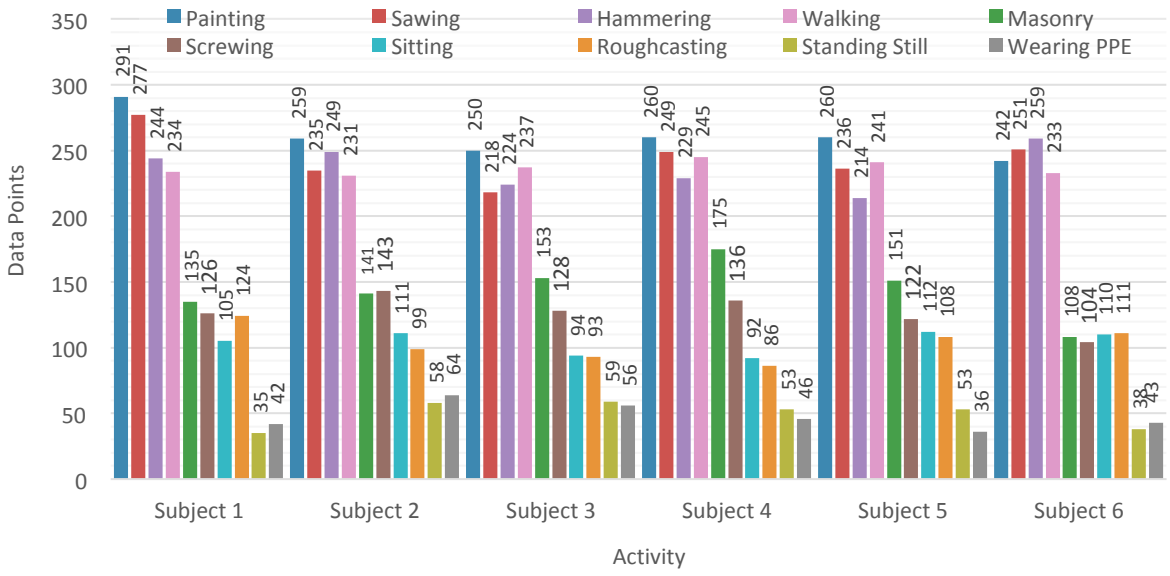


Figure 7.6 – Activities data points. [312]

A total of 155 minutes of activities were monitored. The process of labelling the actions (second by second) took approximately 26 hours of work. Table 7.2 also shows the number of points (variables) collected by the 3-axis accelerometers positioned at three points on the volunteers' bodies.

Table 7.2 – Data collected.

		Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)	**Manual tools (Hammering, Sawing and Screwing)**	**Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking)**	**Total**
Experiment Timing	seconds	3046	3644	2618	9308
	minutes	51	61	44	155
Labelling Timing	minutes	508	607	436	1551
Acceleration data points	Wrists and Leg	27414	32796	23562	83772
	Wrist (dominant)	9138	10932	7854	27924

7.2.3 Data processing

For data processing, pre-labelling of activities is necessary. First, the training of the classification of the algorithms based on machine-learning uses the labelled data. Second, it is with pre-labelling that it becomes possible to quantify the accuracy of the analyses. The multivariate statistical analysis serves to group data groups according to the characteristics of their variables. Both processes were applied to

understand each method's specificities and the potential for future applications. Besides, a graphical analysis of the accelerations collected in the 3-axes is possible, which allows an analysis of the peculiarities of each activity, helping in the perception of the results obtained by the classification methods.

7.2.3.1 Machine-learning

Given the large amount of data collected by electronic devices and, in order to process such information quickly and autonomously, it is necessary to use post-processing based on machine intelligence. Academic studies focusing on the classification of human activities/actions develop algorithms based on Deep Learning [204,294] and Machine Learning [200,297,307].

The general architecture of this methodology can be seen in Figure 7.7 [312]. All data processing tasks, including data segmentation, feature extraction, feature selection, hyperparameter tuning, classifier training, and classifier testing, were performed using Python, particularly the scikit-learn library [312].

After labelling, the activities were divided into three activity groups, and several special classification conditions were studied [312]. These included: the optimal window size to segment the data; the extraction and selection of relevant artificial features; the hyperparameters tuning; and the training and selection of the best performing classifier using a nested cross-validation approach [312]. Each of these steps is described in detail in the following sections. Finally, the best performing classifier was applied in a subject-independent and subject-dependent evaluation of all activities using the selected optimal window [312].

All the data are used to examine the classifier performance when considering small groups of activities, select the best performing classifier, as well as test several special classification conditions [312]. After this initial division, the data was further separated into segments of fixed-length (sliding windows) of four, five and six seconds, each of these segments presented an overlap of 75% between consecutive windows [312]. This results in a total of twelve distinct training sets, one for each group and window combination [312]. The sliding windows approach was selected, taking into account initial tests' performance with a randomly selected group: group two with a 4-seconds window [312].

For each window in this experiment, an artificial feature vector is extracted by calculating time and frequency domain variables [312]. The calculated feature vector involves sixteen attributes: (1) maximum; (2) minimum; (3) sum; (4) mean; (5) mean absolute deviation; (6) standard deviation; (7) variance; (8) kurtosis; (9) entropy; (10) skewness; (11) power; (12) energy; (13) range; (14) interquartile range; (15) signal magnitude area; and (16) cross-correlation of binary combinations of the 3-axis [312]. In total, when accounting for the three accelerometers and respective three axes, 235 features are extracted to compose the feature vector [312].

The employed selection methods were: the ANOVA F-test; Feature Importance; Mutual Information; and Recursive Feature Elimination [312]. Although different methods produce dissimilar results, the voting process's final ranking ensures a suitable selection [312]. As such, by applying this approach, the initial 235 features were reduced to 150, with these selected features delivering around 90% feature importance for all task groups [312].

Regarding the classifiers, thirteen different classifiers were tested [312]. These include eight base models and five ensemble methods, namely: Base models: (1) Decision Tree (DT); (2) K-Nearest Neighbours (KNN); (3) Logistic Regression (LR); (4) Multilayer Perceptron (MLP); and Multiclass Support Vector Machines (SVM) with different kernels [(5) linear (LSVM), (6) polynomial (PSVM), radial basis function – (7) rbf (RSVM), and (8) sigmoid (SSVM)]. Ensemble methods: (9) Random Forest (RF); (10) Extremely Randomized Trees (ExT); (11) AdaBoost (AdB); (12) Gradient Boosting (GrB); and (13) Majority/Hard Voting (Vote) [312].

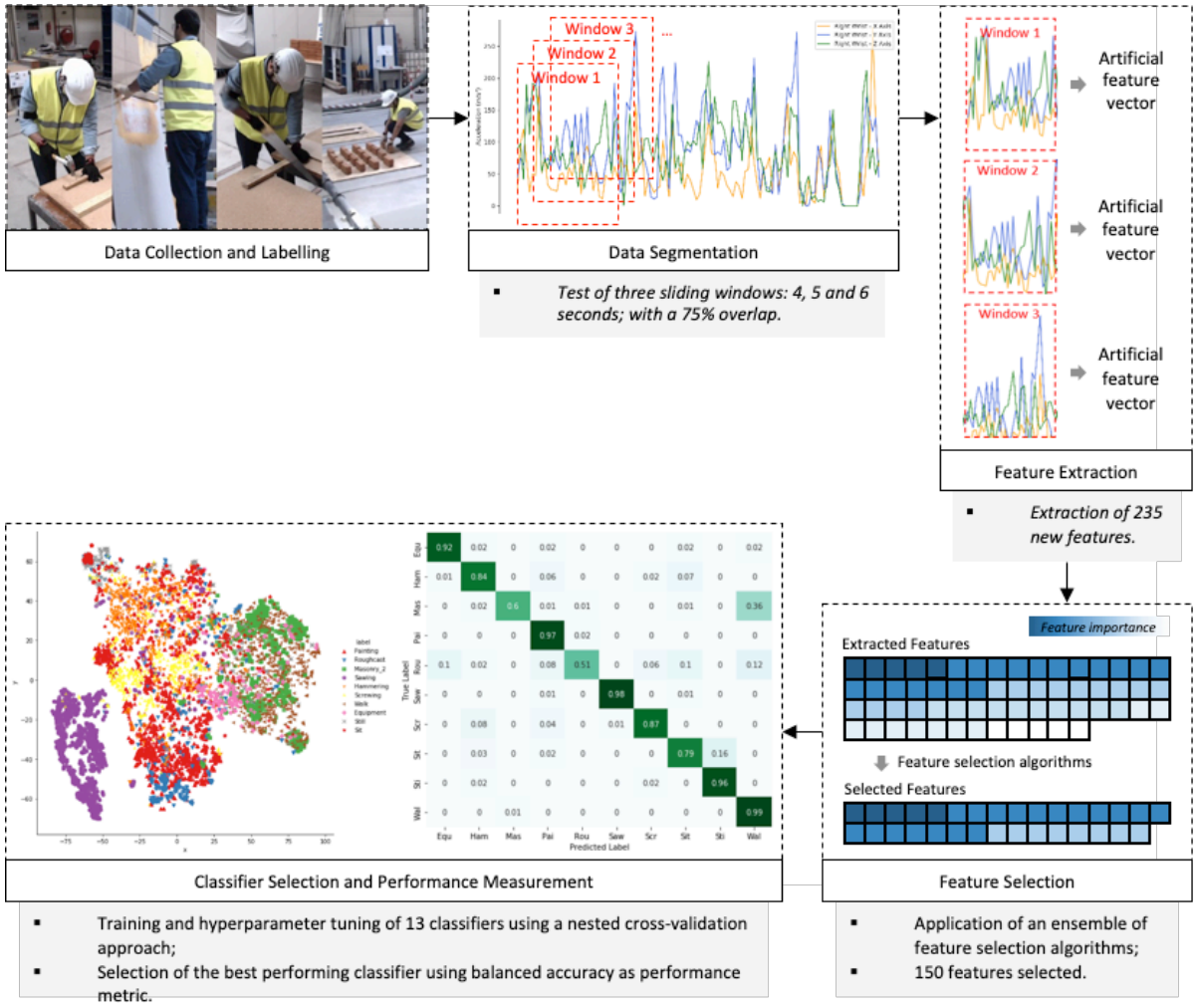


Figure 7.7 – Machine learning method. [312]

7.2.3.2 Multivariate statistical analysis

The purpose of the multivariate statistical analysis is to verify clusters' formation concerning actions collected during the experiment. For the development of the statistical calculations, IBM SPSS Statistics (version 25) software was used mainly, Microsoft Excel software was also used for graphical formatting of data from SPSS and also in the development of charts and figures.

The analysis by non-hierarchical classification allows the evaluation of the dimensionality of the clusters formed by the subjects [174], where a synthesis analysis of the mathematical results is carried out concerning the aspects of the three groups of processes and the ten activities:

- Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting): 3 clusters;
- Manual tools (Hammering, Sawing and Screwing): 3 clusters;
- Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking): 4 clusters.

After applying the non-hierarchical classification according to the number of activities in each group, the results are confronted against the data labelled to determine the accuracy of these processes. Initially, to group the clusters' activities, only the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used as variables (83,772 data points). However, nine features were used in the analysis.

After, the same process was performed only with the values of the accelerations (3-axes) of the volunteers' dominant hand. Thus, the analysis had a third of the number of variables used in the previous case (27,924 data points). However, three features were used in the analysis.

7.2.4 Results and Discussion

7.2.4.1 Machine-learning

Figure 7.8 (a/b) and Figure 7.9 (a) presents the classifiers' performance (average balanced accuracy) for each group and window combination, and Figure 8.9 (b) presents the average performance of all activities together. It can be seen that an overall best performance roughly above 92%, Figure 7.9 (b).

Further, Figure 7.8 (a) shows the group composed by "Free-hand performing" (Masonry) plus two "Manual tools" (Painting and Roughcasting) where the best algorithm accuracy performance is 92.71% (6-seconds window in the LSVM). The group composed only by "Manual tools" (Hammering, Sawing and Screwing) where the best performance is on the 5-seconds window in the Vote with 96.07%, as shown in Figure 4 (b).

Finally, Figure 7.9 (a) shows the group composed by "Do not operating value" (Wearing PPE; Sitting; Standing still) and "Walking" (Walking) where the best performance is for the 6-seconds window 94.66% in the GrB. In summary, all three groups presented a similar range of performance with the best accuracy above 92%.

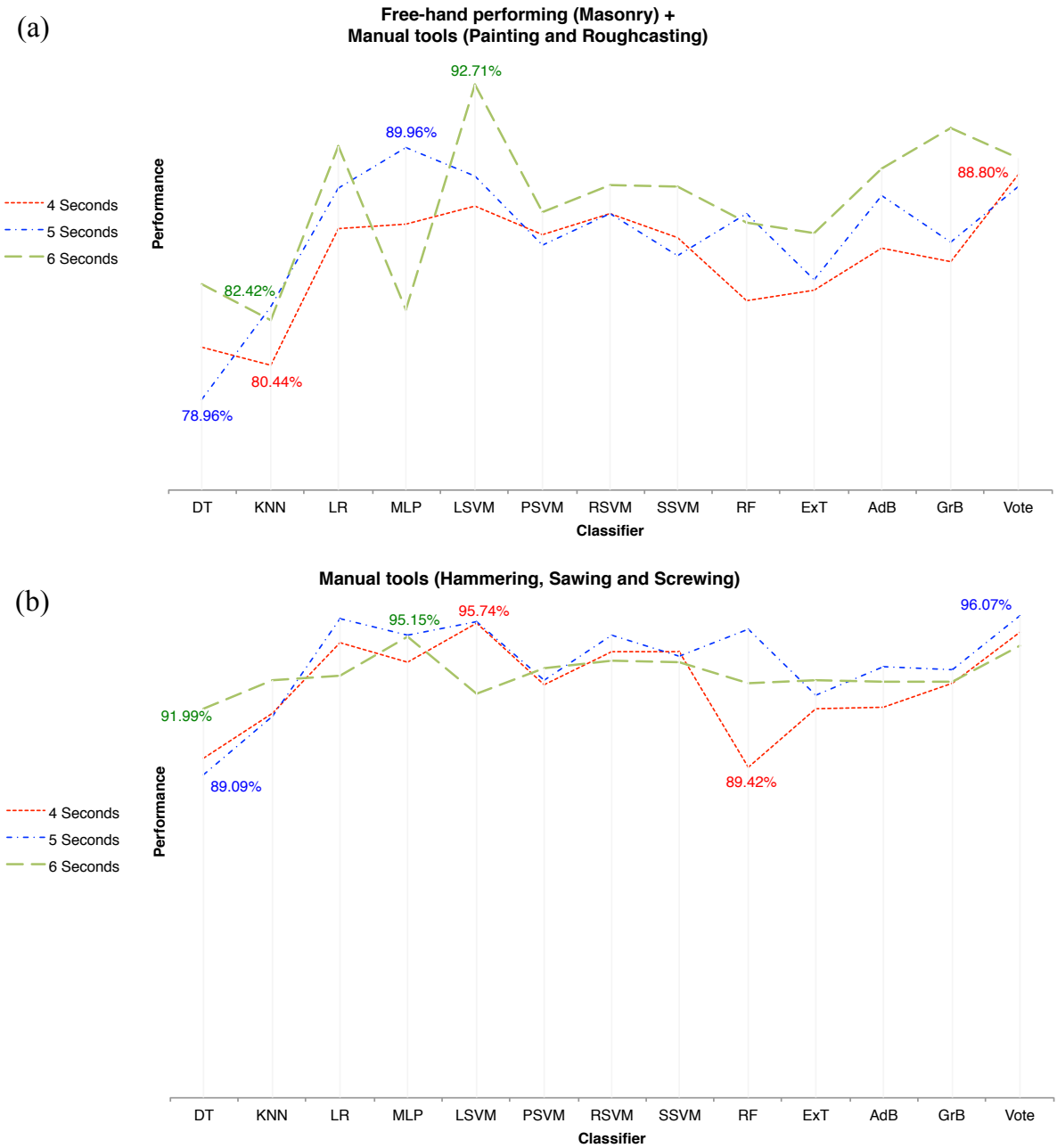


Figure 7.8 – (a) Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting). (b) Manual tools (Hammering, Sawing and Screwing).

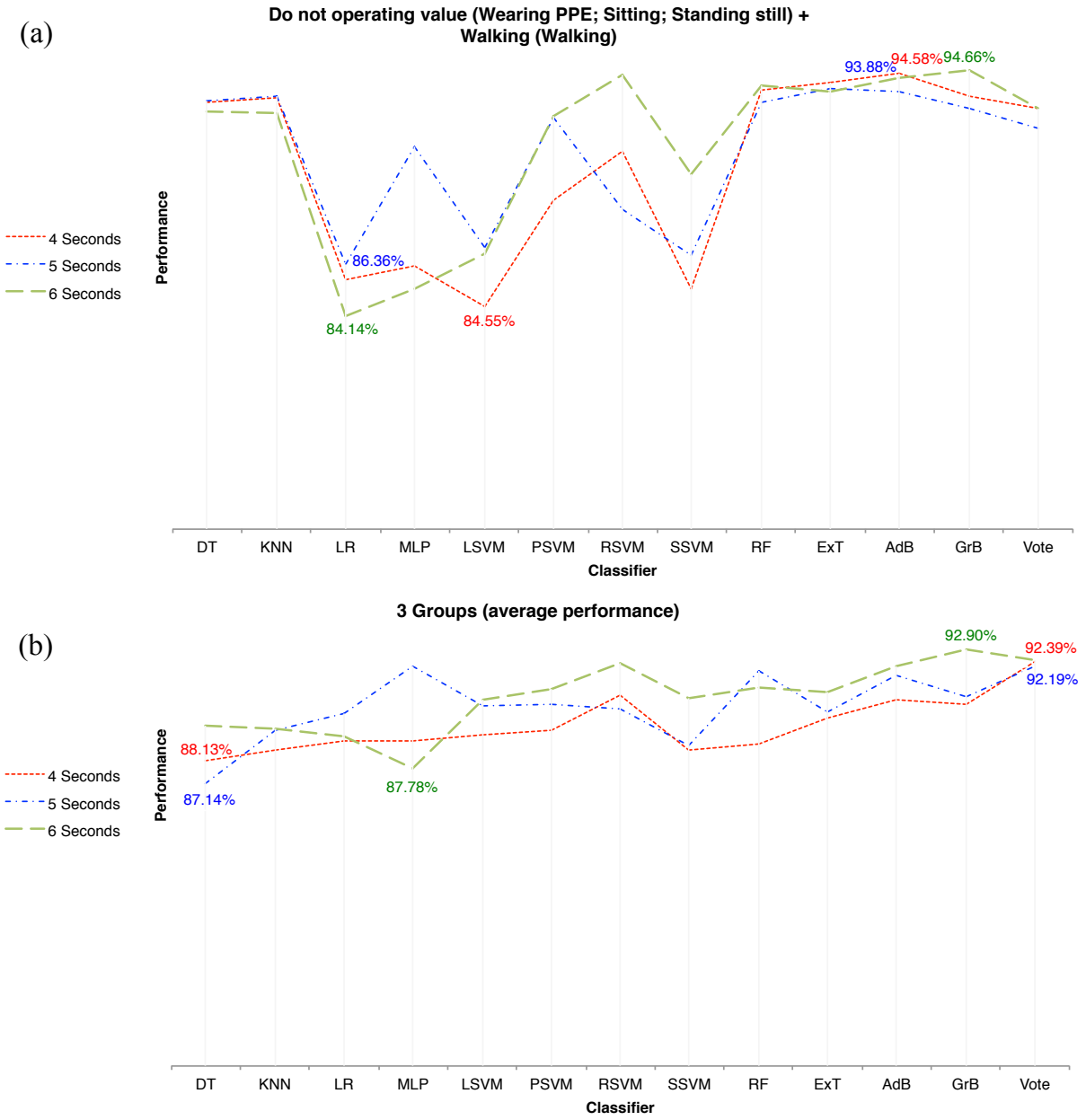


Figure 7.9 – (a) Do not operating value (Wearing PPE; Sitting; Standing still) + Walking (Walking). (b) 3 Groups (average performance).

Figure 7.10 (a) presents the average accuracy for all windows in each group combination. It can be highlighted that the motion is very characteristic when performing "Manual tools" (Hammering, Sawing and Screwing). The free-hand activity (Masonry) is less peculiar, and the lower accuracy can be seen in the group composed by "Free-hand performing" (Masonry) plus two "Manual tools" (Painting and Roughcasting). Finally, the group composed by "Do not operating value" (Wearing PPE; Sitting; Standing still) and "Walking" (Walking) is compound for very different activities, and it can contribute on a unique algorithm' frame.

As previously stated, a subject-dependent approach was used to verify if and how much would the classifier performance benefit from training new subjects (workers) before predicting their activities.

This approach was only applied to all ten activities separately analyse using the 6-seconds window and compared with a subject-independent at the same 6-seconds window. Firstly, comparing the subject-independent approach best results above in the 6-second window for each group (92.71%, 96.07%, 94.66%) against the best result of all ten activities at once at the same subject-independent method of 85.54% (Figure 8.10 b), it can be seen that performance decreased of roughly 10%. Therefore, the process of clustering activities in small groups to process shows as a vital tool to increase accuracy. Furthermore, comparing the subject-dependent approach, the overall average performance increased roughly 6% from the subject-independent approach, reaching 86.08% against 80.43%. The KNN (subject-dependent) classifier achieving the best performance of 93.69% and the AdB classifier ranking in a close second with 93.57%.

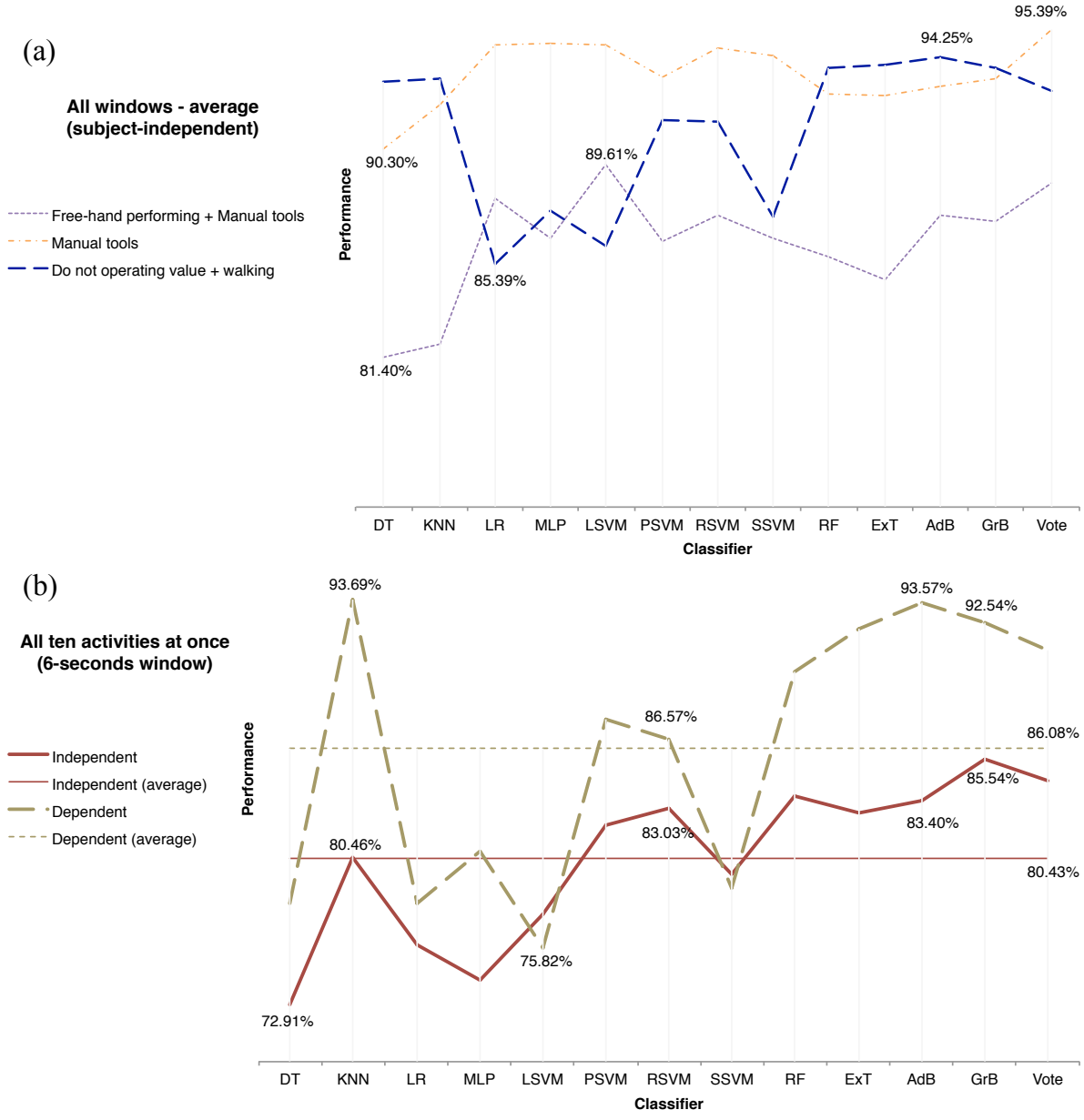


Figure 7.10 – (a) All windows - average (subject-independent). (b) All ten activities at once (6-seconds window).

As results indicated, both approaches can boost system accuracy performance: the subject-independent grouping activities achieved roughly above 92%, and for all ten activities at once analyse by the subject-dependent achieving 93.69%. Furthermore, in the worst-case scenario, the subject-independent approach with all activities reached 85.54% accuracy. As a result, it represents a possible accuracy between 85% and 93% for a system developed on that behaviour.

7.2.4.2 Multivariate statistical analysis

Table 7.3 presents the set-up requirements for non-hierarchical classification in Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting) processes and tasks, making 3 clusters fitting to the activities. In order to group the activities in clusters, the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used as a total of nine variables (27,414 data points).

Table 7.3 – Set-up 3 clusters.

Output Created	**23-MAR-2020 12:43:22**	
Input	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	3046
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any clustering variable used.
Syntax	Wrist (dominant) 3 VAR Wrist (non-dominant) 3 VAR Leg (dominant) 3 VAR	QUICK CLUSTER VAR00006-07-08-09-10-11-12-13-014 /MISSING=LISTWISE /CRITERIA=CLUSTER(3) MXITER(10) CONVERGE(0) /METHOD=KMEANS(NOUPDATE) /SAVE CLUSTER DISTANCE /PRINT INITIAL ANOVA CLUSTER DISTAN.
Resources	Processor Time	00:00:00.39
	Elapsed Time	00:00:00.00
	Workspace Required	1944 bytes
	QCL_2	Distance of Case from its Classification Cluster Centre

Table 7.4 presents the interaction history. Iterations stopped because the maximum number of iterations was performed. The maximum absolute coordinate change for any centre is 0.836, and the current iteration is 10. The minimum distance between the initial centres is 584.024. Table 7.5 shows the distances between the final cluster of activities centres, and Table 7.6 presents the number of cases in each cluster.

Table 7.4 – Interaction history.

	Change in Cluster Centres		
Iteration	**Roughcast**	**Painting**	**Masonry**
1	313.4141	199.5498	246.4082
2	63.2804	25.8395	110.5989
3	26.4273	18.7292	38.7331
4	12.9446	9.3842	15.5661
5	7.7845	5.5610	4.5176
6	3.9339	2.9209	1.3539
7	3.050	2.4074	0.9133
8	1.772	1.3521	0.3767
9	1.1367	0.8386	0.2579
10	0.8516	0.6606	0

Table 7.5 – Distances between final cluster centres.

Cluster	**Roughcast**	**Painting**	**Masonry**
Roughcast		159.1544	283.4235
Painting	159.1544		233.6170
Masonry	283.4235	233.6170	

Table 7.6 – Number of cases.

Number of Cases in each Cluster	
Roughcast	1022
Painting	1309
Masonry	715
Valid	3046
Missing	0

In effect, each of the 3,046 lines (activities identified in each second) was identified by a cluster. A small extraction of this information is shown in Table 7.7. Moreover, a true or false analysis is carried out line by line to identify whether the indicated cluster was equal or not to the real previously labelled. Thus, when the correct results are totalled, the accuracy of the analysis is determined.

Finally, the results for the multivariate analysis of "Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)" indicated 1,855 correct values in 3,064, reaching an accuracy of 60.90%. The same process using clustering just three axes of the dominant hand (9,138 data points) achieves 32.50% accuracy.

Table 7.7 – Verification process.

Subject	Task	Date	Time	Wrist (dominant)			Wrist			Leg			Case N.	Cluster	Distance	Test
1	Masonry	26/02/19	10:40:18	284	117	212	131	123	113	92	40	62	942	Masonry	268.6488	TRUE
1	Masonry	26/02/19	10:40:19	50	66	99	227	110	164	60	119	96	943	Masonry	156.0831	TRUE
1	Masonry	26/02/19	10:40:20	67	63	99	69	65	180	141	135	90	944	Masonry	124.6410	TRUE
1	Masonry	26/02/19	10:40:21	112	83	6	69	80	165	143	135	39	945	Masonry	132.9037	TRUE
1	Masonry	26/02/19	10:40:22	41	59	55	121	93	57	11	55	31	946	Painting	137.2267	FALSE
1	Masonry	26/02/19	10:40:23	201	160	153	43	63	42	12	47	1	947	Roughcast	134.2535	FALSE
1	Masonry	26/02/19	10:40:24	103	119	53	51	192	79	57	131	62	948	Masonry	143.0891	TRUE

Table 7.8 presents the set-up requirements for non-hierarchical classification in Manual tools (Hammering, Sawing and Screwing) process and tasks, making 3 clusters fitting to the activities. In order to group the activities in clusters, the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used as a total of nine variables (32,796 data points).

Table 7.8 – Set-up 3 clusters.

Output Created		**23-MAR-2020 13:53:12**
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	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	3644
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any clustering variable used.
Syntax	Wrist (dominant) 3 VAR Wrist (non-dominant) 3 VAR Leg (dominant) 3 VAR	QUICK CLUSTER VAR00006-07-08-09-10-11-12-13-014 /MISSING=LISTWISE /CRITERIA=CLUSTER(3) MXITER(10) CONVERGE(0) /METHOD=KMEANS(NOUPDATE) /SAVE CLUSTER DISTANCE /PRINT INITIAL ANOVA CLUSTER DISTAN.
Resources	Processor Time	00:00:00.44
	Elapsed Time	00:00:00.00
	Workspace Required	1944 bytes
Variables Created or Modified	QCL_1	Cluster Number of Case
	QCL_2	Distance of Case from its Classification Cluster Centre

Table 7.9 presents the interaction history. Iterations stopped because the maximum number of iterations was performed. The maximum absolute coordinate change for any centre is 0.547, and the current iteration is 10. The minimum distance between the initial centres is 575.296. Table 7.10 shows the distances between the final cluster of activities centres, and Table 7.11 presents the number of cases in each cluster.

Table 7.9 – Interaction history.

Change in Cluster Centres			
Iteration	**Sawing**	**Screwing**	**Hammering**
1	261.0570	345.3322	323.5139
2	58.5810	76.7062	55.8298
3	65.0758	25.0337	21.6352
4	14.4996	11.5637	8.7550
5	3.3059	6.6206	3.7269
6	0.5369	4.2438	2.0083
7	0.4353	2.3990	1.0646
8	0	1.2704	0.5940
9	0	0.7804	0.3616
10	0	0.8472	0.3929

Table 7.10 – Distances between final cluster centres.

Cluster	**Sawing**	**Screwing**	**Hammering**
Sawing		260.6854	244.6953
Screwing	260.6854		108.0933
Hammering	244.6953	108.0933	

Table 7.11 – Number of cases.

Number of Cases in each Cluster		
Cluster	Sawing	1172
	Screwing	783
	Hammering	1689
Valid		3644
Missing		0

Each of the 3,644 lines (activities identified in each second) is identified by a cluster. A small extraction of this information is shown in Table 7.12. Moreover, a true or false analysis is carried out line by line to identify whether the indicated cluster was equal or not to the real previously labelled. Thus, when the correct results are totalled, the accuracy of the analysis is determined. Finally, the results for the multivariate analysis of Manual tools (Hammering, Sawing and Screwing) process and tasks indicated 2,772 correct values in 3,644, reaching an accuracy of 76.07%. The same process using clustering just three axes of the dominant hand (10,932 data points) achieves 76.23% accuracy.

Table 7.12 – Validation process.

Subject	Task	Date	Time	Wrist (dominant)			Wrist			Leg			Case N.	Cluster	Distance	Test
2	Sawing	25/02/19	14:34:47	262	25	46	0	4	0	0	0	0	7	Sawing	29,0162	TRUE
2	Sawing	25/02/19	14:34:48	171	36	35	0	1	0	0	0	0	8	Sawing	108,6854	TRUE
2	Sawing	25/02/19	14:34:49	85	222	152	0	0	0	0	0	0	9	Screwing	138,0763	FALSE
2	Sawing	25/02/19	14:34:50	43	91	314	0	0	0	0	0	0	10	Screwing	215,4279	FALSE
2	Sawing	25/02/19	14:34:51	83	25	81	0	0	0	0	0	0	11	Hammering	82,1257	FALSE
2	Sawing	25/02/19	14:34:52	337	72	32	0	0	0	0	1	1	12	Sawing	63,8884	TRUE
2	Sawing	25/02/19	14:34:53	308	59	12	1	4	8	6	13	61	13	Sawing	73,1490	TRUE
2	Sawing	25/02/19	14:34:54	322	79	15	0	0	4	0	1	13	14	Sawing	59,7263	TRUE
2	Sawing	25/02/19	14:34:55	295	73	18	0	0	0	0	0	0	15	Sawing	37,1193	TRUE
2	Sawing	25/02/19	14:34:56	311	79	8	0	0	0	0	0	0	16	Sawing	54,6523	TRUE

Table 7.13 presents the set-up requirements for non-hierarchical classification: Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking) processes and tasks, making 4 clusters fitting to the activities. In order to group the activities in clusters, the absolute parameters of the accelerations (in their three axes) collected on the wrists and one leg were used as a total of nine variables (23,562 data points).

Table 7.13 – Set-up 4 clusters.

Output Created		23-MAR-2020 14:17:23
Input	Active Dataset	DataSet0
	Filter	<none>
	Weight	<none>
	Split File	<none>
	N of Rows in Working Data File	2618
Missing Value Handling	Definition of Missing	User-defined missing values are treated as missing.
	Cases Used	Statistics are based on cases with no missing values for any clustering variable used.
Syntax		QUICK CLUSTER VAR00006-07-08-09-10-11-12-13-014 /MISSING=LISTWISE /CRITERIA=CLUSTER(4) MXITER(10) CONVERGE(0) /METHOD=KMEANS(NOUPDATE) /SAVE CLUSTER DISTANCE /PRINT INITIAL ANOVA CLUSTER DISTAN.
Resources	Processor Time	00:00:00.37
	Elapsed Time	00:00:00.00
	Workspace Required	2288 bytes
Variables Created or Modified	QCL_1	Cluster Number of Case
	QCL_2	Distance of Case from its Classification Cluster Centre

Wrist (dominant) 3VAR
Wrist (non-dominant) 3VAR
Leg (dominant) 3VAR

Table 7.14 presents the interaction history. Iterations stopped because the maximum number of iterations was performed. The maximum absolute coordinate change for any centre is 3.637, and the current iteration is 10. The minimum distance between the initial centres is 531.495. Table 7.15 shows the distances between the final cluster of activities centres, and Table 8.16 presents the number of cases in each cluster.

Table 7.14 – Interaction history.

	Change in Cluster Centres			
Iteration	**Standing still**	**Walking**	**Wearing PPE**	**Sitting**
1	253.1632	271.7627	253.8942	247.4363
2	34.6668	23.8132	28.9162	41.9111
3	15.3285	11.9069	30.5345	16.2089
4	12.8381	4.6949	37.3199	9.3450
5	11.1022	6.0636	29.6576	8.6092
6	9.2294	3.8355	19.1764	5.9783
7	7.2804	3.4810	15.1276	5.1283
8	7.4817	1.9499	12.9699	4.6997
9	6.0755	0.8473	10.0764	5.9705
10	3.6753	1.3617	6.6054	5.3191

Table 7.15 – Distances between final cluster centres.

Cluster	**Standing still**	**Walking**	**Wearing PPE**	**Sitting**
Standing still		272.6942	185.9325	362.6586
Walking	272.6942		190.9127	162.3144
Wearing PPE	185.9325	190.9127		228.9966
Sitting	362.6586	162.3144	228.9966	

Table 7.16 – Number of cases.

Number of Cases in each Cluster		
Cluster	Standing still	763
	Walking	742
	Wearing PPE	725
	Sitting	388
Valid		2618
Missing		0

As well as the processing, each of the 2,618 lines (activities identified in each second) is identified by a cluster. A small extraction of this information is shown in Table 7.17. Moreover, a true or false analysis is carried out line by line to identify whether the indicated cluster was equal or not to the real previously labelled. Thus, when the correct results are totalled, the accuracy of the analysis is determined. Finally, the results for the multivariate analysis of "Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking)" indicated 1,249 correct values in 2,618, reaching an accuracy of 47.71%. The same process using clustering just three axes of the dominant hand (9,138 data points) achieves 46.60% accuracy.

Table 7.17 – Validation process.

Subject	Task	Date	Time	Wrist (dominant)			Wrist			Leg			Case N.	Cluster	Distance	Test
4	Walking	26/02/19	15:29:51	53	39	145	175	27	193	19	33	47	930	Wearing	163,6731	FALSE
4	Walking	26/02/19	15:29:52	110	68	286	96	32	41	25	77	60	931	Wearing	210,4327	FALSE
4	Walking	26/02/19	15:29:53	74	46	100	77	76	140	97	130	50	932	Walking	89,6969	TRUE
4	Walking	26/02/19	15:29:54	124	48	73	22	99	208	115	175	28	933	Walking	156,9528	TRUE
4	Walking	26/02/19	15:29:55	112	57	72	71	164	245	103	197	29	934	Walking	198,7402	TRUE
4	Walking	26/02/19	15:29:56	58	126	233	68	188	302	104	168	38	935	Sitting	283,6098	FALSE
4	Walking	26/02/19	15:29:57	52	121	101	127	157	168	213	163	44	936	Sitting	156,8391	FALSE
4	Walking	26/02/19	15:29:58	55	80	47	89	156	90	214	72	46	937	Walking	172,9138	TRUE

Tables 7.18 and 7.19 presents a summary of all analyses. The process Manual tools with the three activities (Hammering, Sawing, and Screwing) achieve higher accuracy in both situations, Wrists and Leg (76.07%), and Wrist-dominant (76.23%).

Also, it was the only case, of the highest accuracy just clustering the Wrist-dominant data. As seen, the group of two processes and three activities, "Free-hand performing (Masonry) + Manual tools (Painting, Roughcasting)" achieve an accuracy of 60.90% (Wrists and Leg) and (32.50%). In this case, the analyses by just the wrist-dominant data decrease almost to a half.

Finally, the lowest accuracy was identified on the group of two processes and four activities, "Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking)" 47.41% and 46.60% respectively for Wrists and Leg and Wrist-dominant data. In this case, it has shown a slight difference.

It can be seen that in the formation of group "Free-hand performing (Masonry) + Manual tools (Painting and Roughcasting)" when only the data of the dominant wrist occurred a high increase on the maximum absolute coordinate change for any centre. Also, the distances between the final cluster centres decrease significantly. This is not verified in the other two cases, which maintained approximate values in both scenarios.

Forward, a summary analysis will be performed regarding the characteristics of each activity. Moreover, how much the motions patterns of each one of them influence the classification accuracy's performance.

Table 7.18 – Results summary.

Data		Free-hand performing + Manual tools	Manual tools	Do not operating value + Walking	Average	Median
Accuracy	Wrists and Leg	60.90%	76.07%	47.41%	61.46%	60.90%
	Wrist (dominant)	32.50%	76.23%	46.60%	51.78%	46.60%
	Difference	> 28.4%	< 0.16%	> 0.81%		
Acceleration data points	Wrists and Leg	27414	32796	23562		
	Wrist (dominant)	9138	10932	7854		
The maximum absolute coordinate change for any centre	Wrists and Leg	0.836	0.547	3.637		
The minimum distance between initial centres	Wrists and Leg	584.024	575.296	531.495		

Table 7.19 – Results summary (continued).

Data		Free-hand performing + Manual tools	Manual tools	Do not operating value + Walking
Distances between final cluster centres	i	159.1544	260.6854	272.6942
	ii	283.4235	244.6953	185.9325
	iii	233.6170	108.0933	362.6586
	iv			190.9127
	v			162.3144
	vi			228.9966
	Average	225.3983	204.4913	233.9182
The maximum absolute coordinate change for any centre	Wrist (dominant)	9.536	1.041	9.544
The minimum distance between initial centres	Wrist (dominant)	512.347	512.347	481.594
Distances between final cluster centres	i	131.3473	241.3922	163.2217
	ii	205.7065	107.7671	192.3734
	iii	128.8105	257.2948	271.5576
	iv			120.2651
	v			111.9096
	vi			195.5329
	Average	155.2882	202.1514	175.8099

7.2.5 SUMMARY

Figure 7.11 presents the accuracy achieved by the machine-learning process and the multivariate statistical analysis. The classifications made through machine-learning reached high precision in the three cases. How much multivariate statistical analysis was moderately accurate. Forward it is carried out a case-by-case analysis in which it seeks to assess the differences between the classification using the three collection points, and the one carried out only with the wrist-dominant data. Where it is trying to explain why only in the first group there is a loss of approximately 50% of accuracy and in another case (Manual tools), there is a subtle increase in accuracy and at the last group only a difference of less than 1%.

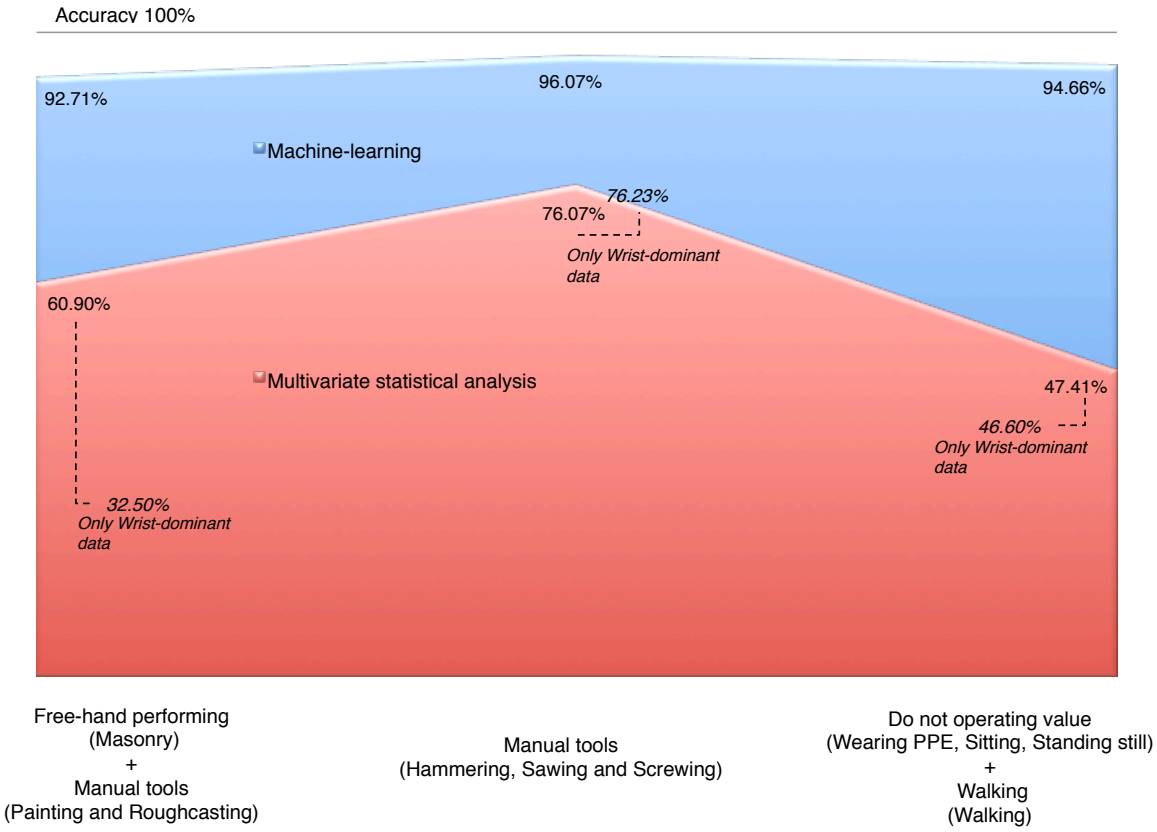


Figure 7.11 – Machine learning vs. Multivariate statistical analysis.

The Masonry activity presents a mix of motions, from loading the bricks to the laying. Therefore it is possible to observe a variety of accelerations in the three axes (X, Y, Z) in both the dominant and non-dominant hands and the leg (Figures 7.12, 7.13 and 7.14).

In contrast, the Painting activity has a component with more significant action in the dominant hand, with a marked acceleration in the vector Z, with little or no action in the other hand and legs (Figures 7.15, 7.16 and 7.17).

Finally, in Roughcasting activity, dominant hand movements' predominance can be identified with more significant accelerations in vectors Z and X (Figures 7.18, 7.19 and 7.20). It can be inferred that when classifying these three activities, some confusion occurs because of the non-linearity of the masonry activity.

Moreover, this becomes even clearer when in the significant loss of accuracy of the analysis based only on the wrist-dominant motions, as the leg variable that will differentiate it from the others is lost. However, Figure 7.21 shows the heterogeneity of the motions acceleration groups of the analysis activities.

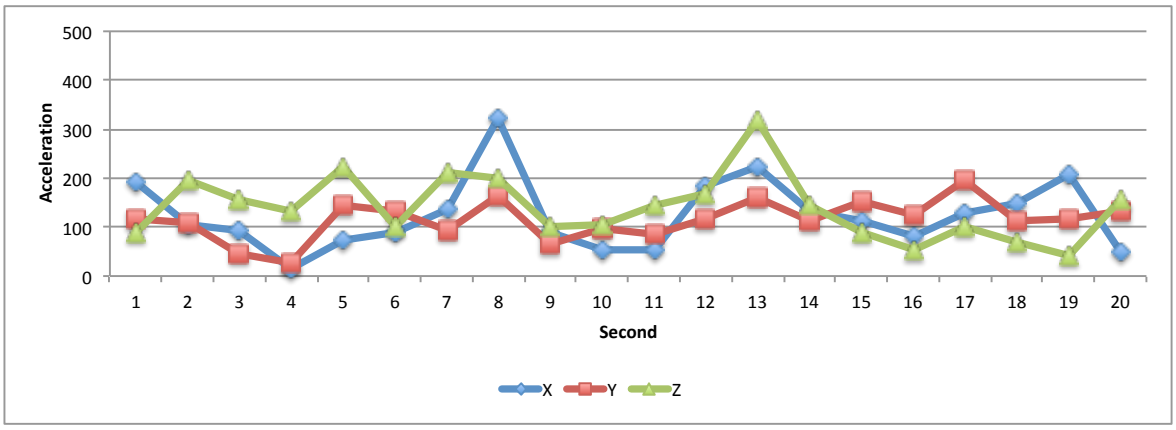


Figure 7.12 – Masonry (wrist-dominant).

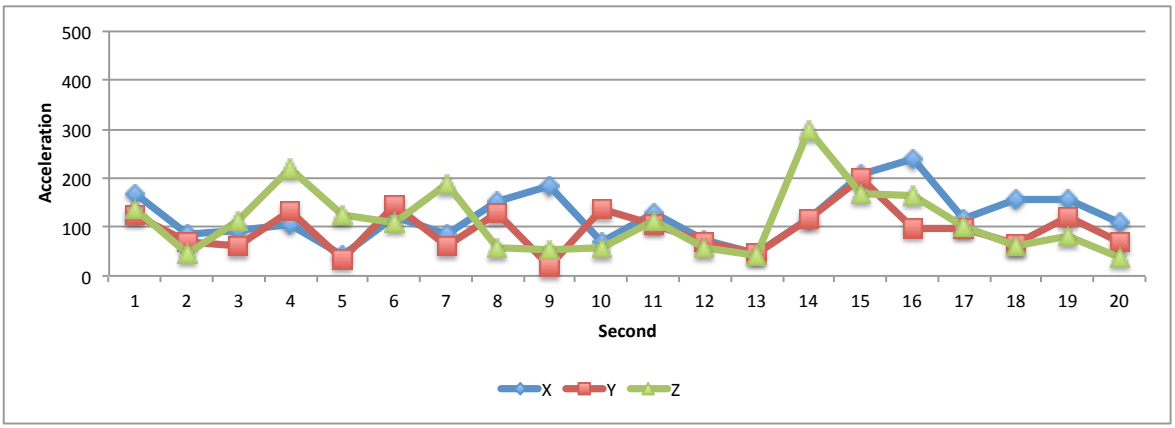


Figure 7.13 – Masonry (wrist non-dominant).

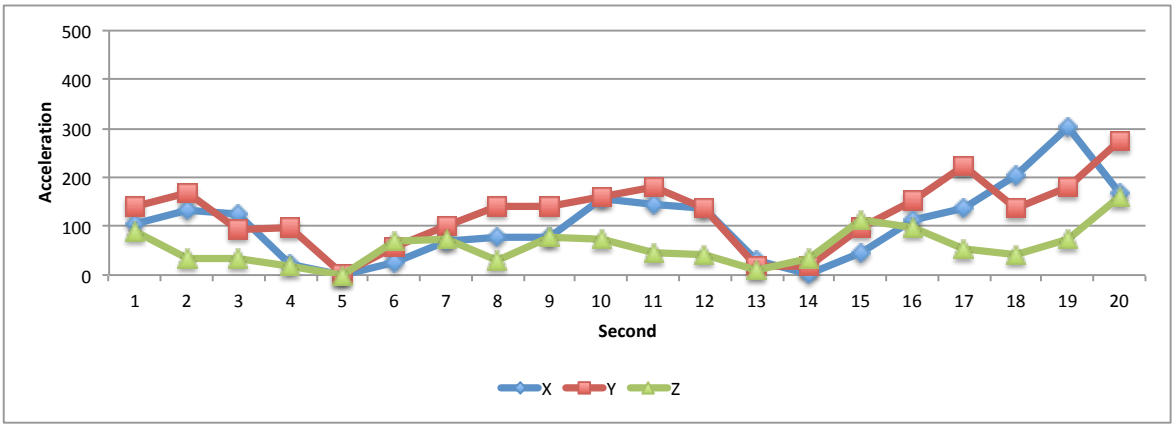


Figure 7.14 – Masonry (leg-dominant).

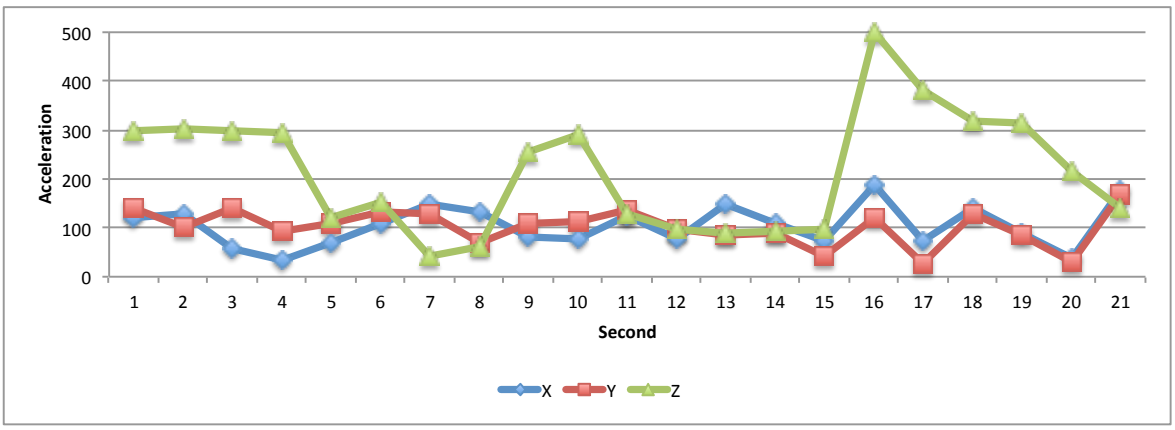


Figure 7.15 – Painting (wrist-dominant).

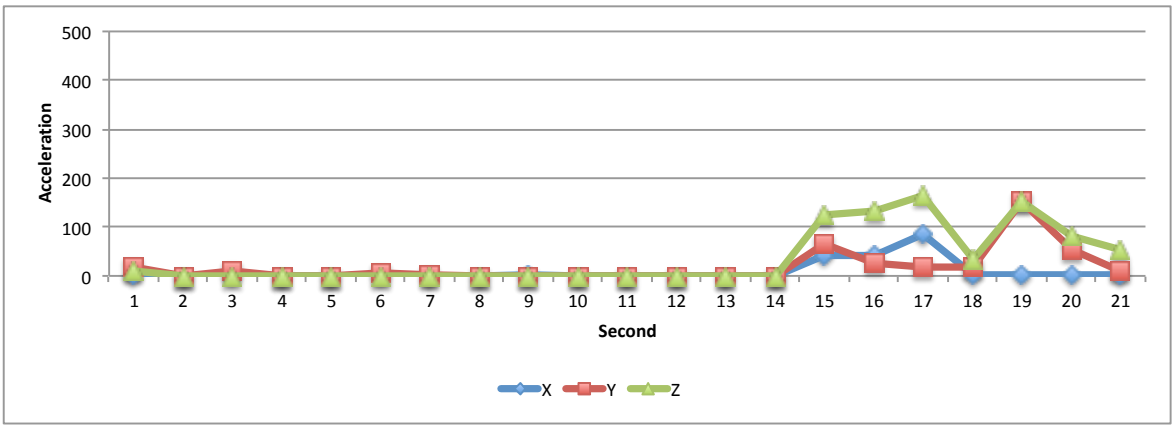


Figure 7.16 – Painting (wrist non-dominant).

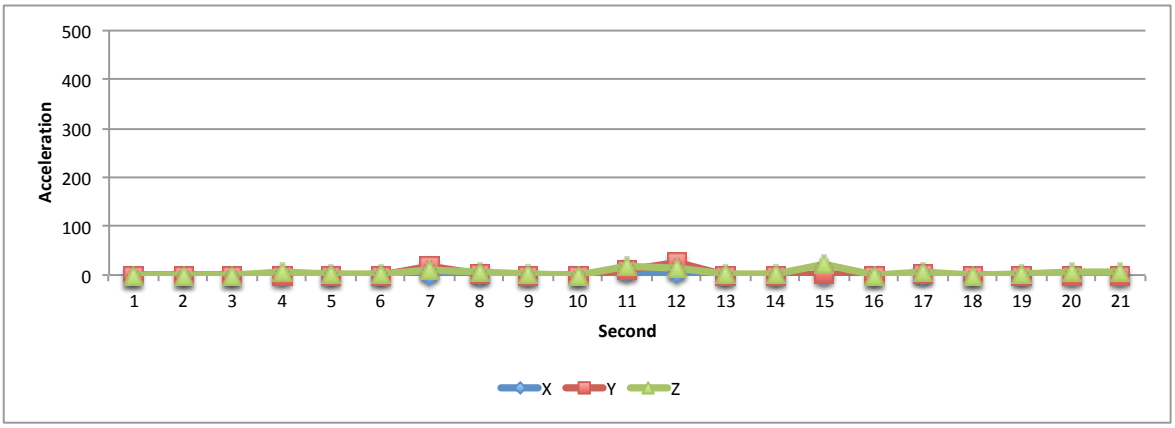


Figure 7.17 – Painting (leg-dominant).

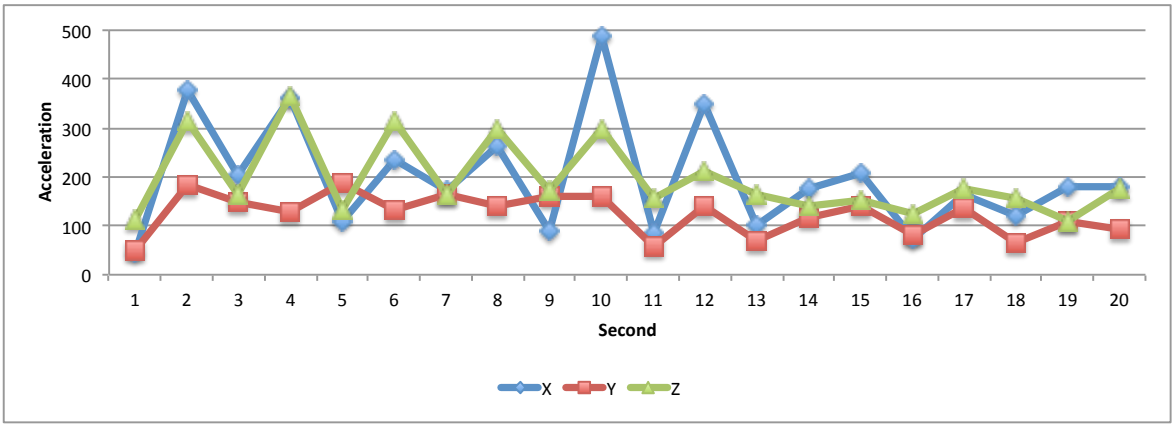


Figure 7.18 – Roughcast (wrist-dominant).

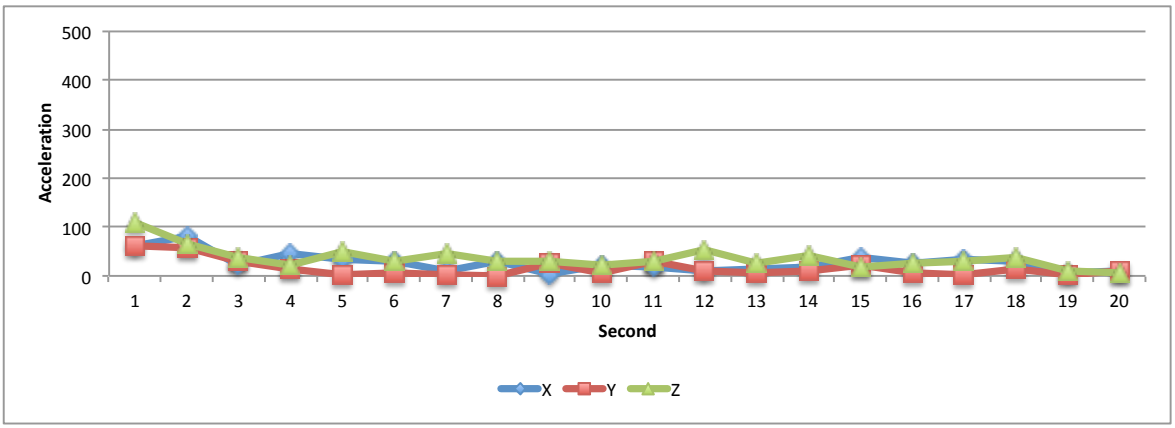


Figure 7.19 – Roughcast (wrist non-dominant).

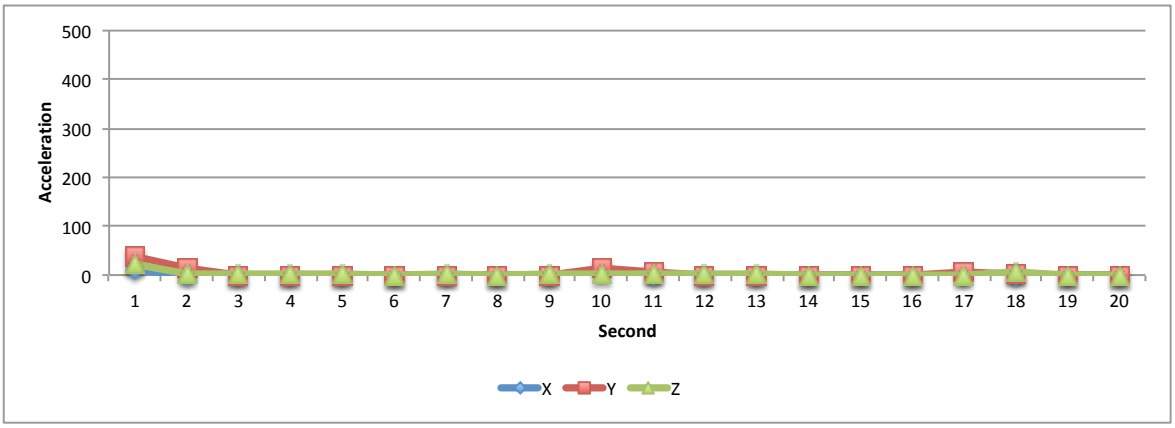


Figure 7.20 – Roughcast (leg-dominant).

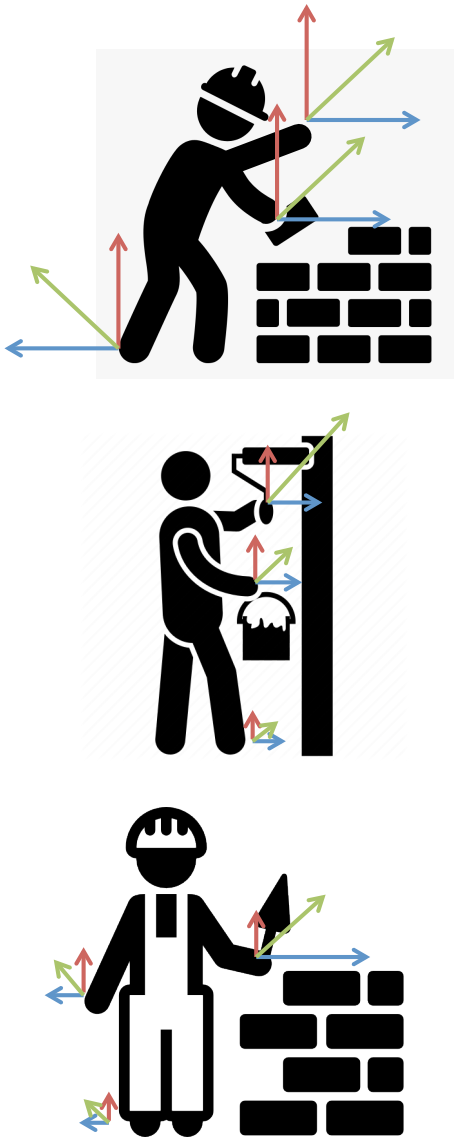


Figure 7.21 – Free-hand performing (Masonry) + Manual tools (Painting, Roughcasting).

In the case of grouping, only activities with the use of manual tools, a more precise classification/clustering are observed. All three activities have similar characteristics, with significant dominant hand motions, with non-dominant hand support when adjusting the material/element and supporting the body, with virtually no legs' motions.

It stands out in the activity of hammering the predominance of movement in vector X and also in Z (Figures 7.22, 7.23, 7.24). In the sawing motions, the predominance of acceleration in vector X is latent (Figures 7.25, 7.26, 7.27). Finally, when screwing, a linear pattern is seen, with the predominance of vectors Y and Z (Figures 7.28, 7.29, 7.30). Figure 7.31 presents this set of activities graphically. However, it is observed that the accuracy of the classifiers is not influenced by the non-analysis of the motions of the non-dominant hand and leg. On the contrary, there is a subtle increase in the accuracy.

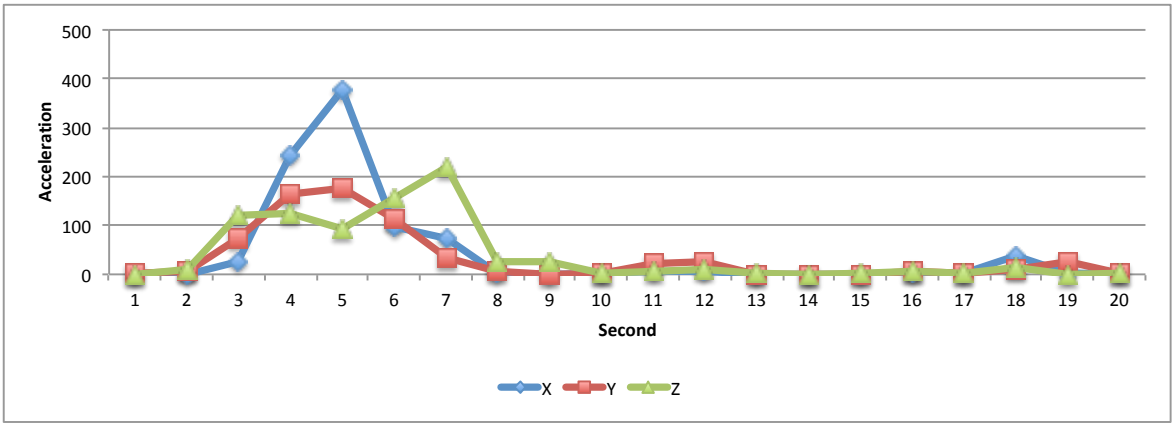


Figure 7.22 – Hammering (wrist-dominant).

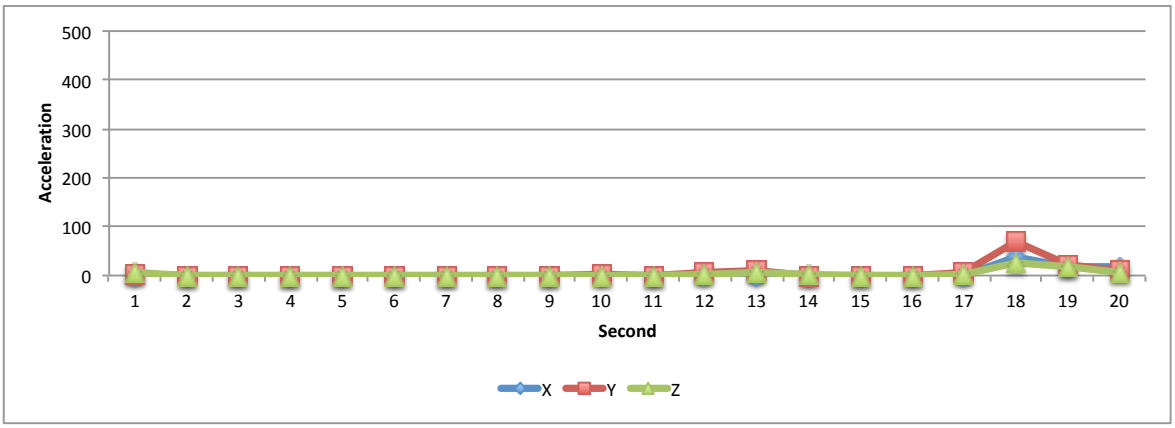


Figure 7.23 – Hammering (wrist non-dominant).

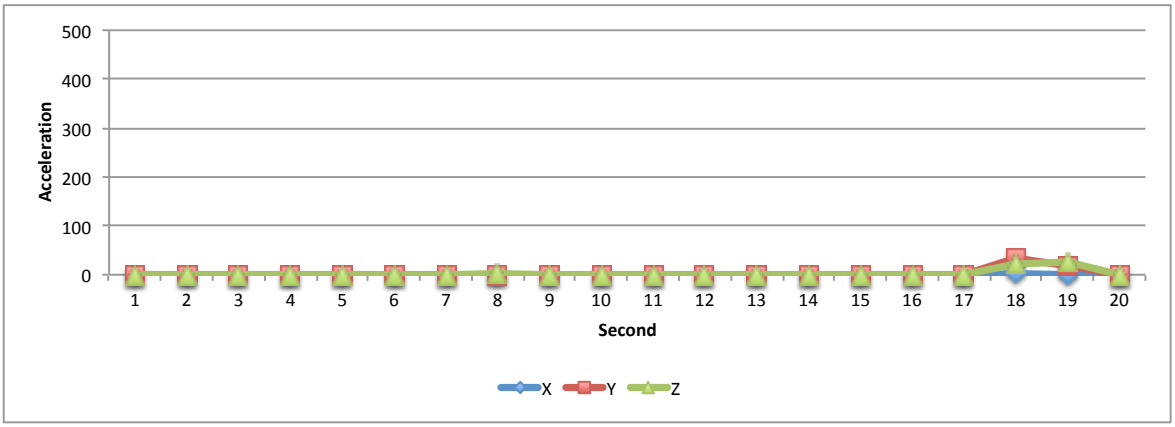


Figure 7.24 – Hammering (leg-dominant).

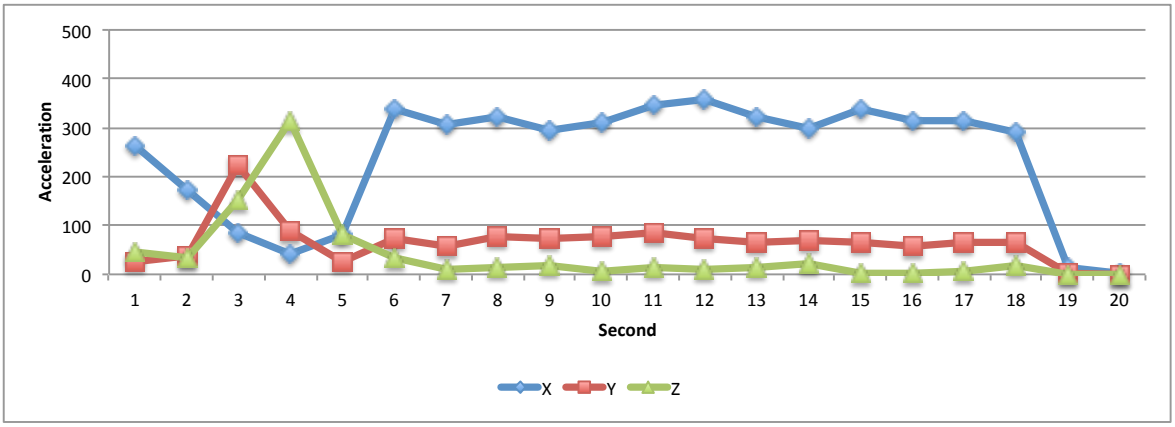


Figure 7.25 – Sawing (wrist-dominant).

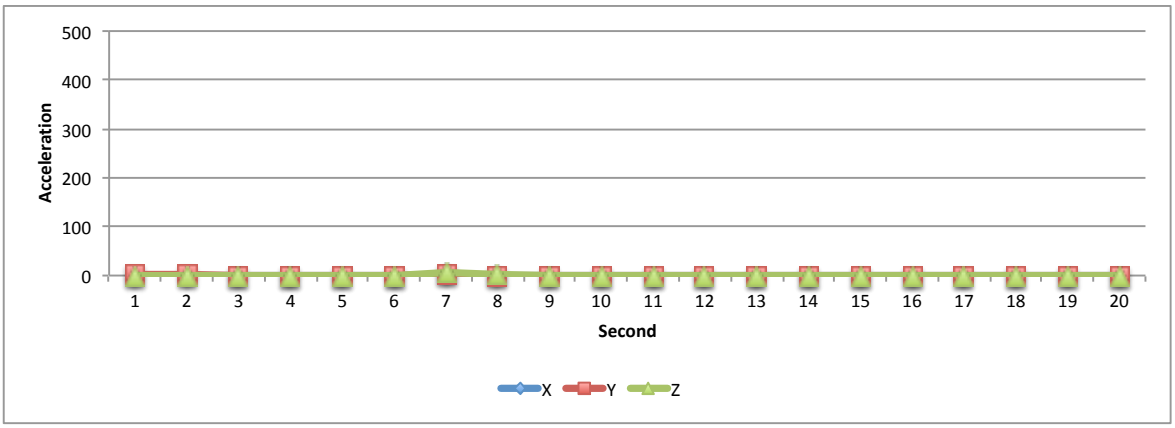


Figure 7.26 – Sawing (wrist-non dominant).

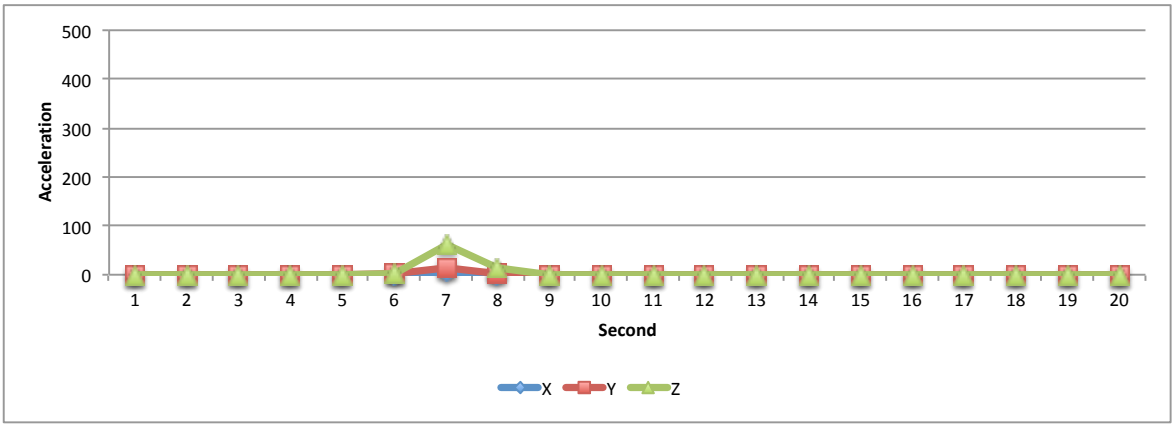


Figure 7.27 – Sawing (leg-dominant).

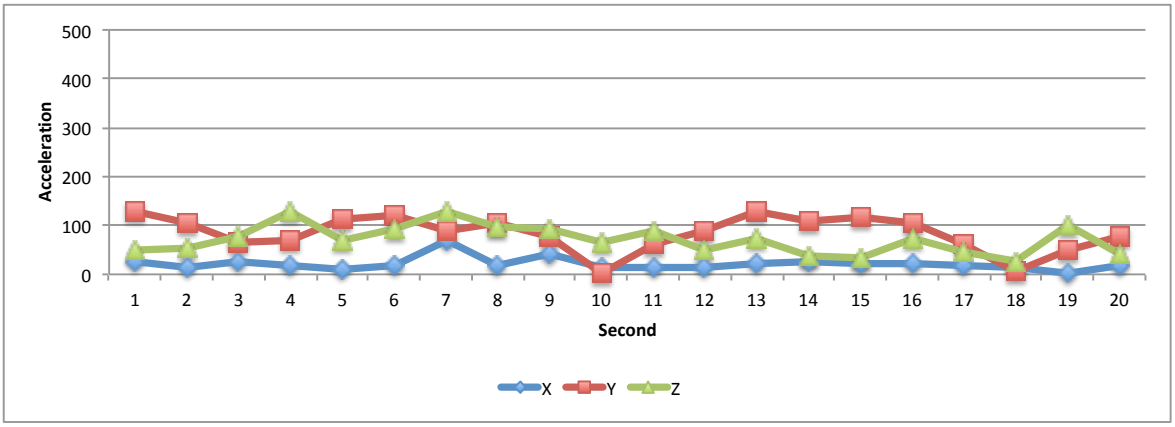


Figure 7.28 – Screwing (wrist-dominant).

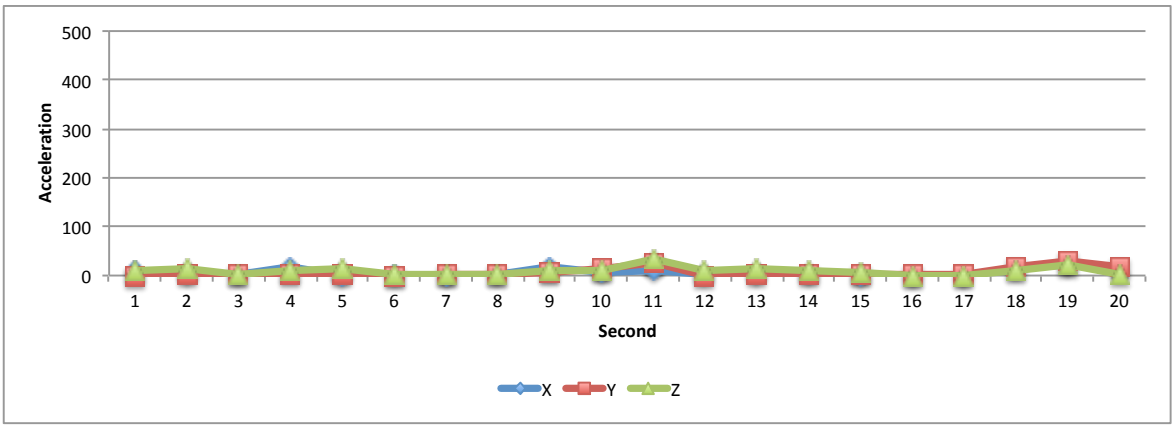


Figure 7.29 – Screwing (wrist-non dominant).

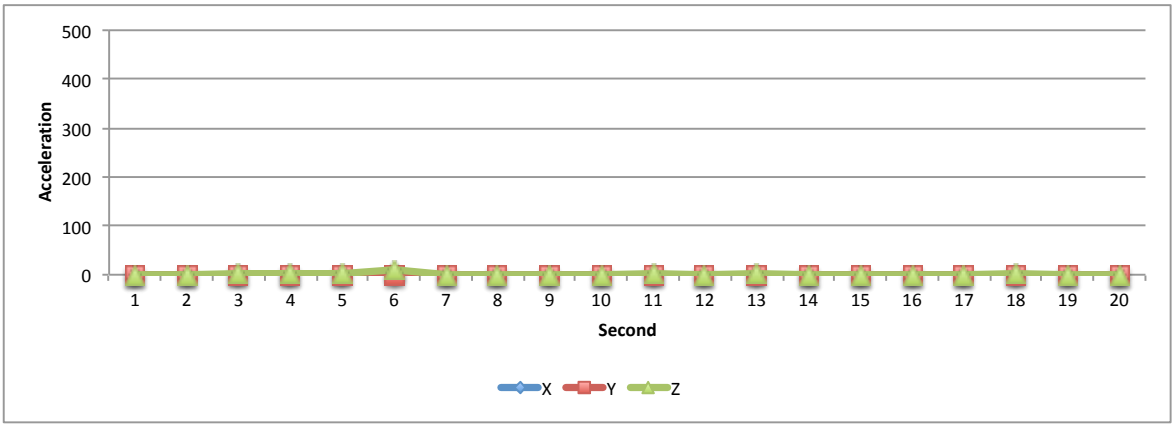


Figure 7.30 – Screwing (leg-dominant).

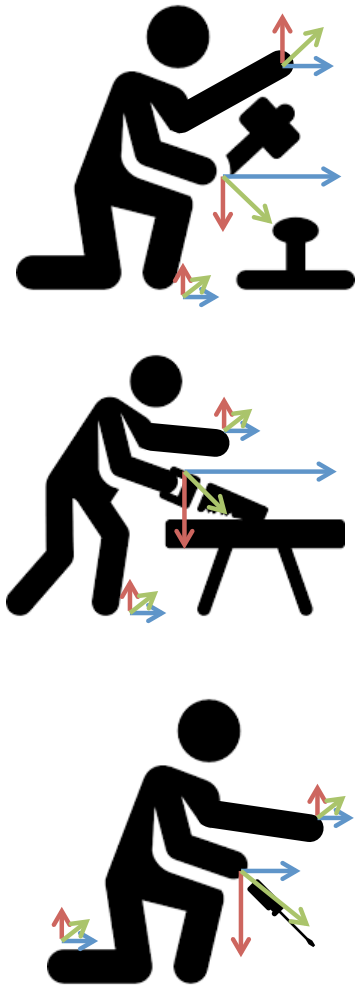


Figure 7.31 – Motion characteristic of Manual tools (Hammering, Sawing and Screwing).

Therefore, except for the activity Standing still, which practically does not present motions with representative accelerations (Figures 7.38, 7.39, 7.40). The other activities are of peculiar motions. For example, even while Sitting, volunteers move their hands and a few their legs (Figures 7.35, 7.36, 7.37).

When Wearing PPE, no significant legs' motions are detected, but the hands have practically random accelerations (Figures 7.32, 7.33, 7.34). When Walking, the limbs' motions and accelerations have an even similar cadence in each individual (Figures 7.41, 7.42, 7.43).

What is found is that machine-learning, as it has a higher simulation capacity, more accurately interprets the acceleration patterns. On the contrary, the simple grouping by multivariate analysis only makes it easy to observe the Standing still state, not evaluating/testing cadences with similar acceleration. Figure 7.44 seeks to graphically convey the most prominent vectors in each of the activities. When the results are only pertinent to the wrist-dominant data, it can be seen that there are

practically no differences in the accuracy. This fact indicates that the wrist-dominant motion detected was peculiar enough to differentiate such different actions.

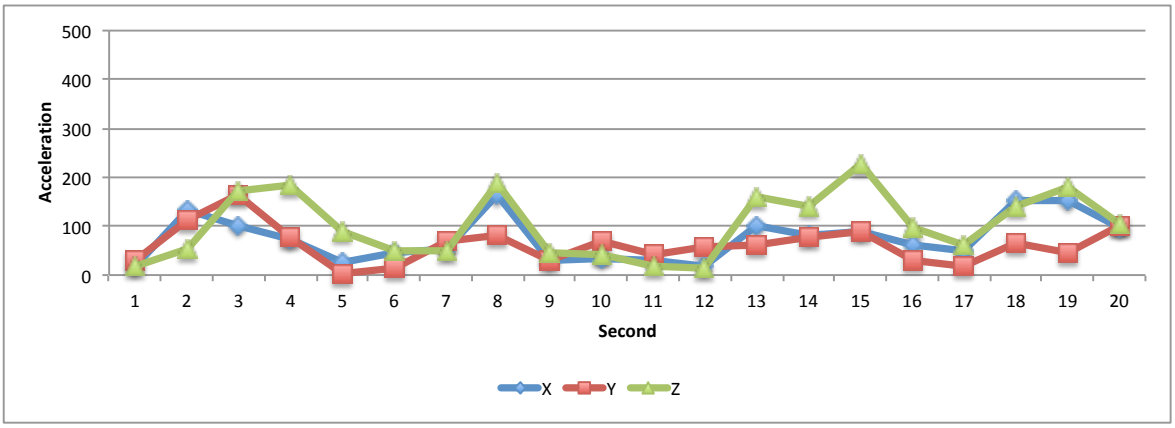


Figure 7.32 – Wearing PPE (wrist-dominant).

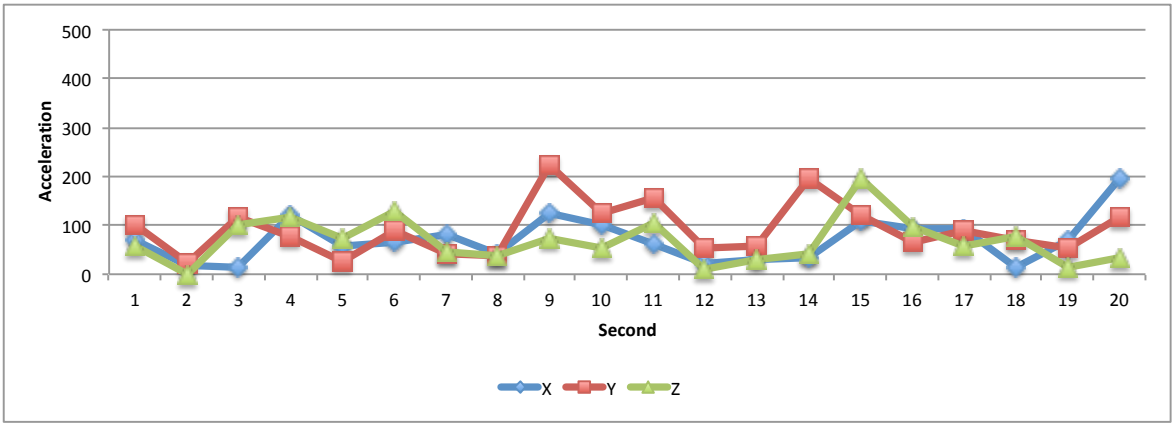


Figure 7.33 – Wearing PPE (wrist non-dominant).

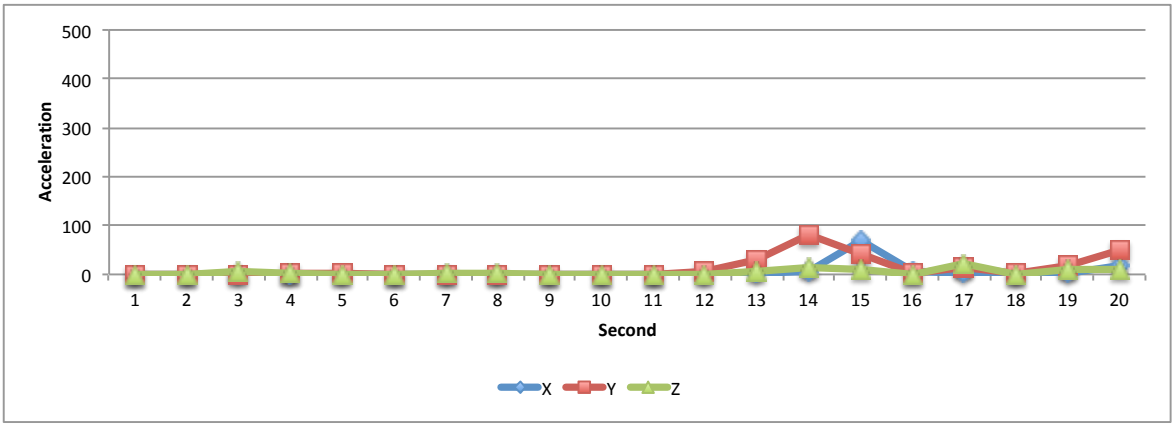


Figure 7.34 – Wearing PPE (leg-dominant).

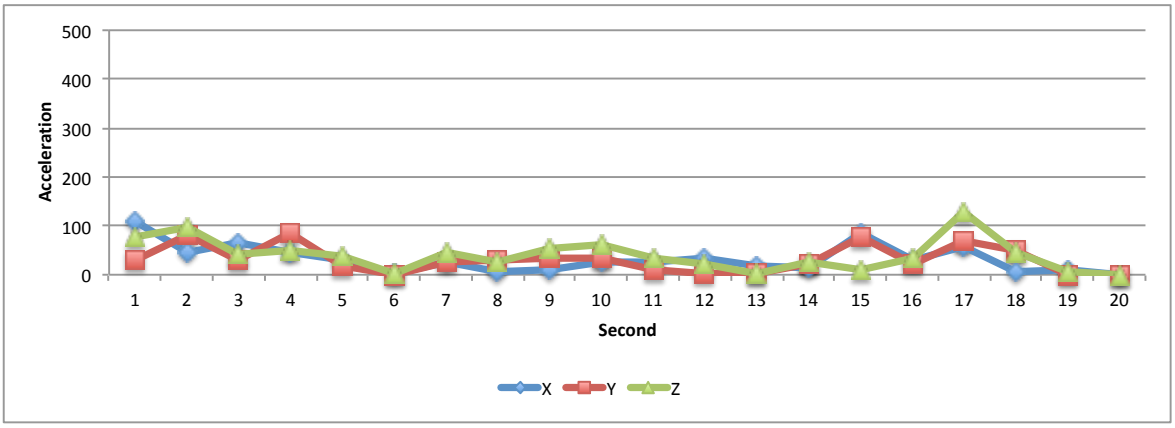


Figure 7.35 – Sitting (wrist-dominant).

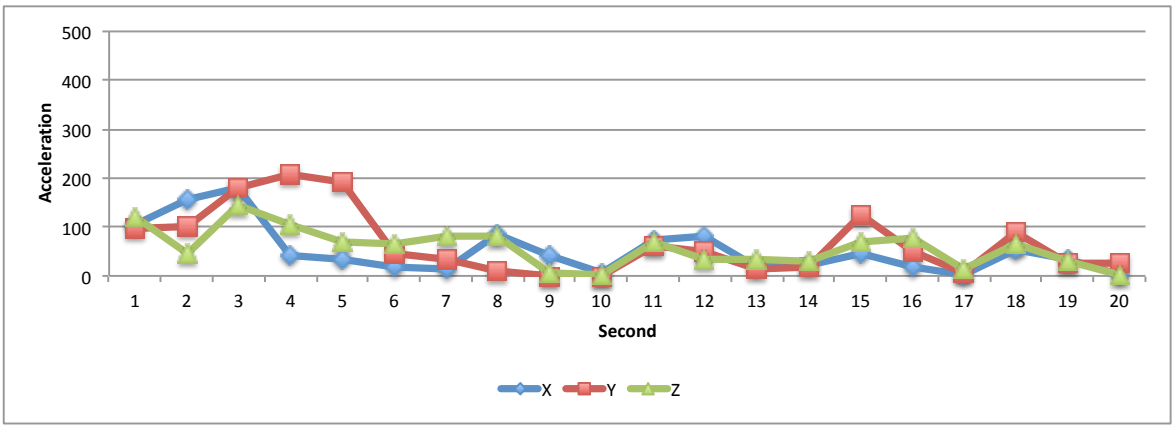


Figure 7.36 – Sitting (wrist-non dominant).

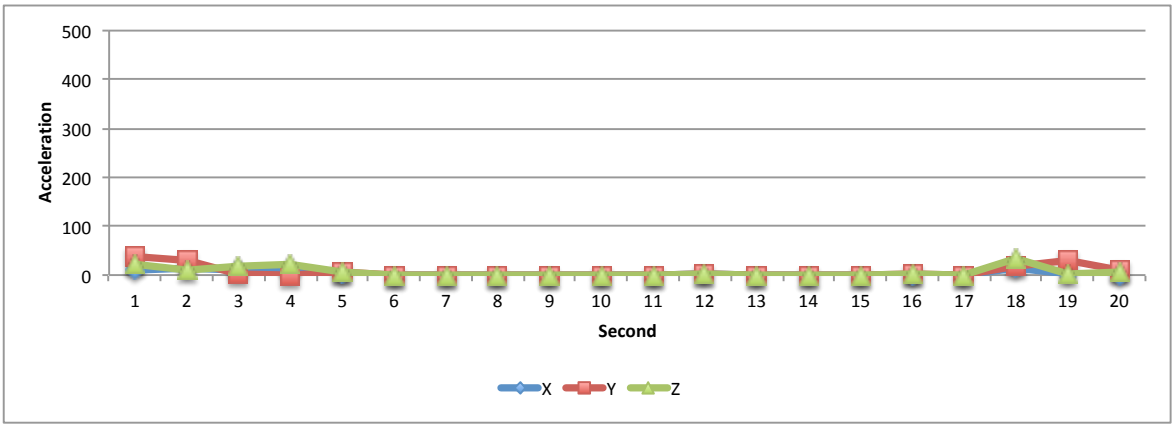


Figure 7.37 – Sitting (leg-dominant).

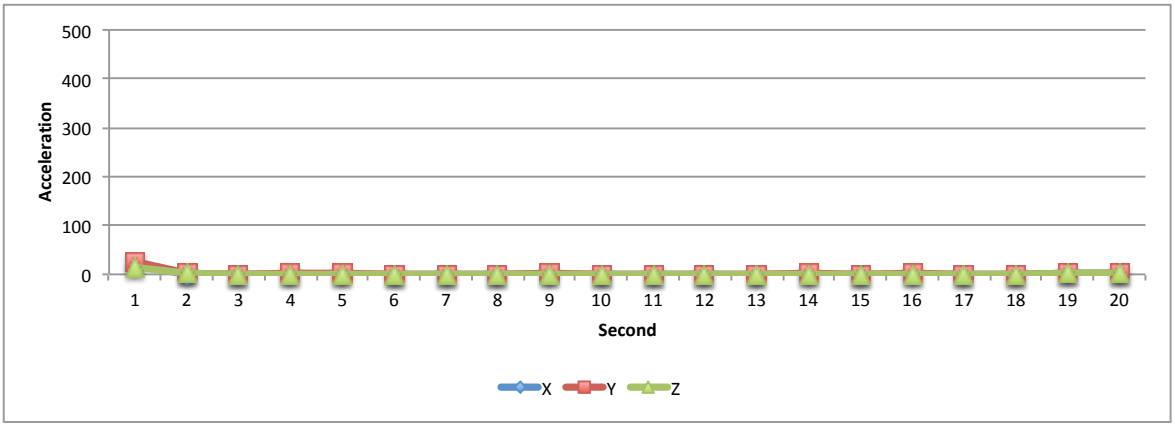


Figure 7.38 – Standing still (wrist-dominant).

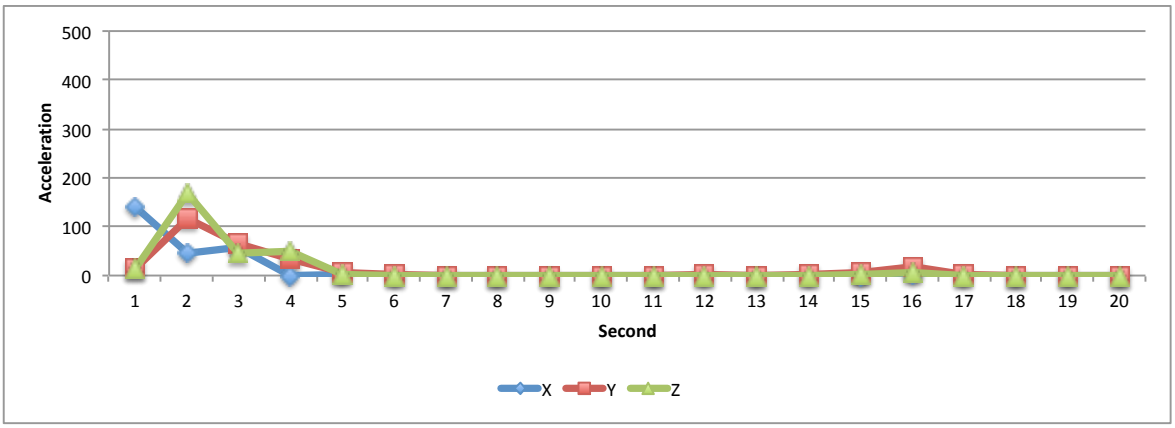


Figure 7.39 – Standing still (wrist non-dominant).

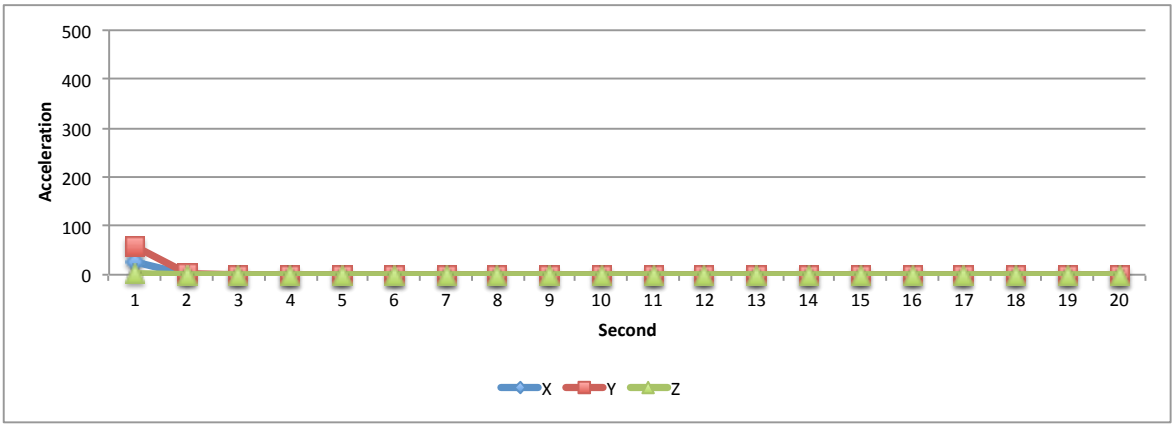


Figure 7.40 – Standing still (leg-dominant).

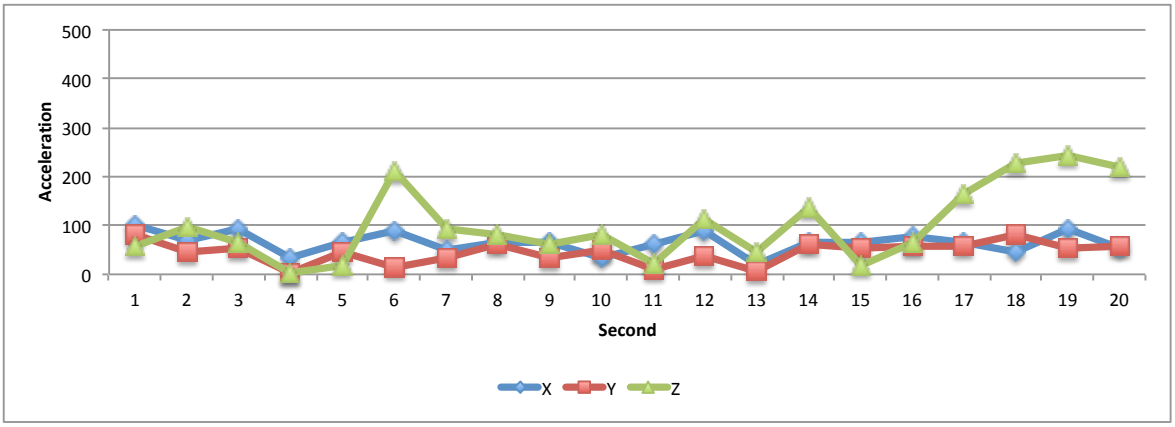


Figure 7.41 – Walking (wrist-dominant).

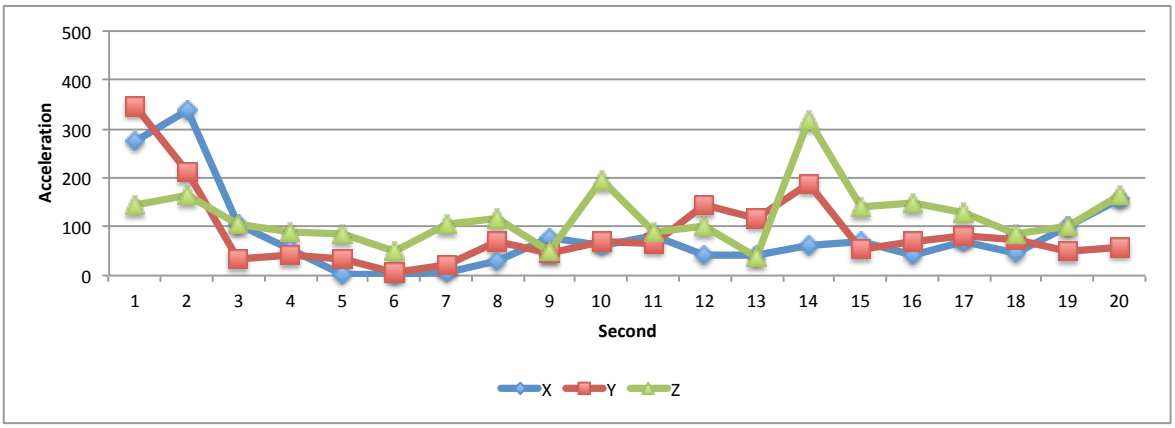


Figure 7.42 – Walking (wrist non-dominant).

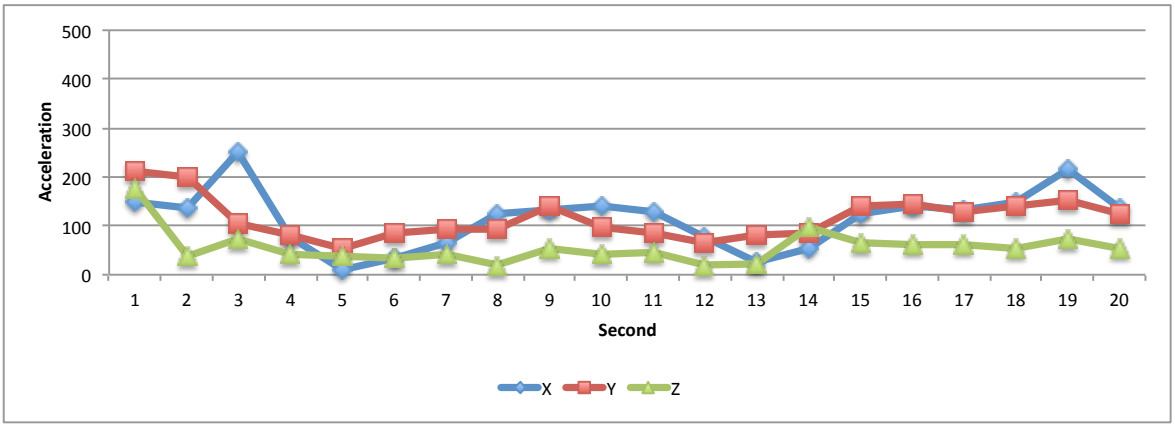


Figure 7.43 – Walking (leg-dominant).

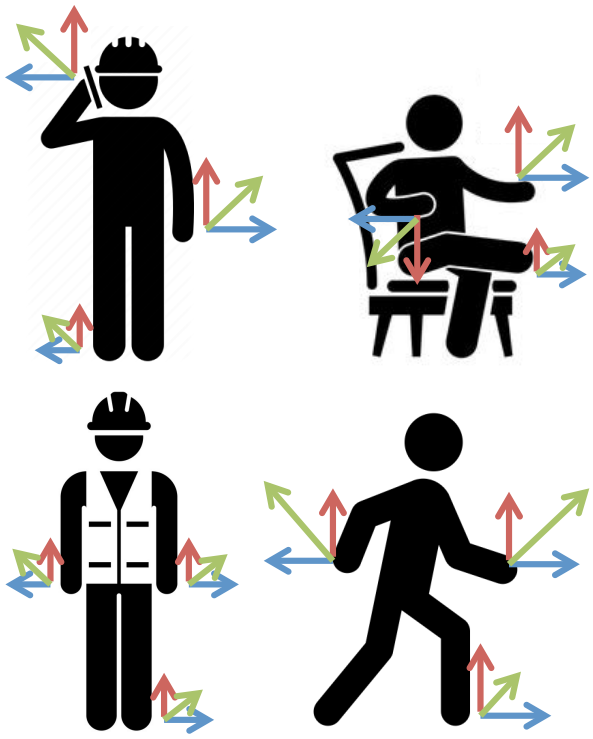


Figure 7.44 – Do not operating value (Wearing PPE, Sitting, Standing still) + Walking (Walking).

Finally, based on the results and the data classification process's perception, it is possible to make a qualitative evaluation of the machine-learning methods and multivariate statistical analysis (Figure 7.45). The great purpose of these classifiers is to avoid manual data processing, because in practice (in a real-life construction situation), the large volume of data would result in extensive manual work.

	Pre-labelling	Features (processed)	Accuracy	Computational demand	Expert knowledge	Training sets to process	Standalone algorithm
Machine Learning	yes	235 (initially) 150 (filtered)	very high 94%	very high	high	yes	yes
Multivariate Statistical Analysis	yes	9 (3x 3-axis) 3 (1x 3-axis)	moderate 60%	low	low	no	no

Figure 7.45 – Qualitative evaluation.

It can be concluded that the multivariate statistical analysis method alone is not able to replace the need to label actions (in this case, every second). However, multivariate analysis can help facilitate

labelling work since a preliminary process can seek to cluster the data and facilitate its visual interpretation. The multivariate analysis method is more straightforward than machine-learning and can achieve a moderate accuracy with fewer features to vectorize, also demanding lower expert knowledge and computational capacity. The enormous potential of machine-learning is the creation of algorithms that, once able to interpret an activity (based on acceleration), can perform this task without the need for pre-labelling nor training sets. The idealized format of an activity circuit can assist in the algorithms' calibration since a new individual can be monitored in a known sequence of activities/actions. Given the advent of new artificial intelligence mechanisms, as an example, agent-based simulation plus reinforcement learning (which does not require excessive training sets of the algorithms) most enhances the application of data processing through AI.

The option of not linearly grouping the activities proved to be essential for the analysis since it was demonstrated that having heterogeneous motions/acceleration activities creates a difficulty in the classification. Moreover, this is the real picture of the work situations of the craft workers on-site.

7.3 MOTION PRODUCTIVITY ON-SITE CONSTRUCTION ASSESSMENT

Finally, due to several limitations related to the carrying out of experiments on-site, mainly related to the temporality of the case of public calamity caused by the pandemic COVID-19. It should be noted that, as previously planned, it was not possible to carry out the monitoring of workers in acts of training in the Portuguese centre (CICCOPN). The CICCOPN (*Centro de Formação Profissional da Indústria da Construção Civil e Obras Públicas do Norte*) has not carried out on-site training activities from December/2019 until July/2020 and remains unanticipated. For this reason, it has not yet been possible to establish autonomous processes for processing the collected data.

The experiments carried out on-site used the work sampling methodology to evaluate the production processes and test the proposed models' feasibility. Some workers will wear electronic devices and be interviewed to have their impressions about using these devices and the consequences of collecting their performance data. It should be noted that, due to the limited time, these collected data will not be processed.

7.3.1 DATA ANALYSIS METHODS

The work sampling approaches allow the assessment of productivity based on workers' activities observation [22,90–92,160]. Another example of techniques human-observation-based, it can highlight the normative methodology for productivity measurement, the multi-factor model for productivity measurement, and the multiple criteria technique for productivity measurement [22].

In the work sampling methodology, the data is collected through the human observation randomly performed is stratified according to the set of process/actions pre-established [22,90–92,160]. It is essential to point out that this method is based only on the number of observations made, not requiring time-taking or any other verification. It should be noted that the increase in the number of observations recorded is directly related to the increase of the confidence limit and the reduction of the error limit of modelling.

The number of observations in each variable is transformed into a percentage value based on the total observation ratio. According to Meyers and Stewart (2002), the minor proportional item (process/action) in the analysis should indicate the sample size, the "P" as presented in the Equation

(2) [160]. For example, for a 95% confidence, and 5% accuracy if the smallest element percentage is 1%, it is needed at least 152,127 observations, if it is 10% 13,830 observations will be necessary.

$$N = \frac{Z^2\,(1-P)}{(P)(A^2)} \qquad (2)$$

Where:

N = the number of observations needed;

Z = the number of standard deviations requires for a specific confidence level; 90% (1.645), 95% (1.960), 99% (2.575);

P = the minor value proportion of an element in the analysis;

A = the accuracy desired. Most of the time, the study uses ±5% accuracy.

A large number of observations are necessary to validate the analysis statistically makes its execution very difficult, since the construction industry is based on projects with a beginning-end and not on processes continued as manufacturing. This particularity of the construction sector reinforces the usefulness of EPM methods for the collection of data related to productivity.

The purpose of the data collection procedure was to detect workers' activities based on the Worker 4.0 motion productivity model. Observations are taken on a timely basis, whether or not timing is registered, but assuring the worker's action was marking is performing at the very moment of observation. During the data collection of the experiments, random observations of each worker's activity occurred in a time not less than 3 minutes for the same worker by the same researcher.

The crew number of observations was account for as pre-established for the analysis, as frames Table 7.20. The analysis conducted will first indicate the estimated ratios (proportion of each process). The sequence will indicate the number of observations needed for statistical validation (lowest proportion). With nine processes, a lower ratio on the smallest element in the analysis is expected, subsequently indicating a large number of observations.

The proper calculations of the proportions based on the processes and their characteristics will be developed and the calculation of the W4MP Mechanization index. All values will be statistically validated only when the minimum of necessary observations is reached. According to Adrian (2004), the Labour Rating Factor (LRF) is the proportion of the productive state (see Equation 3) [91]. Also, adding 25% of the Contributory/Support Work can determine a rating factor more suitable for crews, here named Labour Rating Factor plus Contributory Work (LRF-C) presented in Equation 4 [91]. Finally, for masonry tasks, it will be demonstrated the connection between the W4MP processes and the assessment of production rates (Man-hour/m2) collecting during the experiment.

$$LRF = \frac{Number\ of\ observations\ of\ productive\ state}{Total\ number\ of\ observations} \qquad (3)$$

$$LRF - C = \frac{Number\ of\ observations\ of\ productive\ state + .25\ supporting\ state}{Total\ number\ of\ observations} \qquad (4)$$

Table 7.20 – Labelling the observations.

W4MP	Acronym	Process	Productive State	N. Observations	Proportion
Free-hand performing	FHP	Operation	Productive or Direct work	xx	x%
Auxiliary tools	AUT	Inspection	Contributory or Support work	xx	x%
Manual tools	MNT	Operation	Productive or Direct work	xx	x%
Electric/Electronic tools	EET	Operation	Productive or Direct work	xx	x%
Machines operation	MOP	Operation	Productive or Direct work	xx	x%
Robotic automation	RBA	Operation	Autonomous Production	xx	x%
Do not operating value	IDL	Delay	Nonproduction work	xx	x%
Walking	WLK	Delay	Nonproduction work	xx	x%
Carrying	CAR	Transportation/ Storage	Contributory or Support work	xx	x%

7.3.2 WATER SUPPLY SYSTEM (TO CONSUMERS' TAPS)

The work consisted of the requalification of the system to the distribution of water for homes and commercial establishments. The activities requirements and, the machines/tools applied will be detailed in the next section. For these activities, only the processes that each craft worker performs at the observed moment will be analysed.

7.3.2.1 Data collection and Sample

Data was collected between 2020/6/6 and 2020/6/15 for one researcher. In average, five to seven workers were observed at once point of view. The activities basically consisted of mechanized disruption of the existing pathway's pavement, removal of this pavement, mechanical excavation and removal of soil, placement of pipes and branches, backfilling, and mechanical compaction of the soil. In street services, the stone pavement and curbs were recomposed.

A total of 1,164 observations were collected. Different machines (e.g. walk-behind vibratory-plate compactors) and equipment (e.g. compact backhoe) wore observed as seen in Figure 7.46. As presented in Figure 7.47, multiple activities can be seen in a frame.

The work was conducted for multiples areas, and it allowed the observation of different stages of the service as an example, workers tasks with manual tools and free-hand motions as captured in Figure 7.48. A wheelbarrow, hand shovel, hammer, bucket, rubber hammer, brush, hoe, are examples of manual tools and accessories used by the craft workers (Figure 7.49).

Finally, Figure 7.50 highlighted that these tasks were characteristic of the multiple machines, vehicles, and craft workers at the same site.



Figure 7.46 – Machine operation and multiple processes.



Figure 7.47 – Workforce performing multiple processes.



Figure 7.48 – Workers performing with manual tools and free-hand motions.



Figure 7.49 – Manual tools and accessories.



Figure 7.50 – Machines, vehicles, and workers.

7.3.2.2 Discussion and findings

Based on the Worker 4.0 Motion Productivity (W4MP), Table 7.21 presents the classification of the sampled crew's performance, collected through the work sampling methodology. It can be seen that the lowest proportion was the EET (Electric/Electronic tools), not counting the Robotic automation not observed at all. Tanking into account the Equation (2) for statistic validation of the sample in that methodology the value of 0.86% indicates a sample needed of 177,328 observations (confidence level of 95% and accuracy of 5%).

Because of this, it cannot be said that this sample represents the total piping task performance population. However, although the results cannot be ratified statistically, it can be inferred that the results point to the workers' occupation/performance during the experiment time.

It is observed that among the nine processes the most observed was the IDL (Do not operating) with 32.30%, followed respectively by MOP (Machine operation) 19.59% and MNT (Manual tools) 18.47%. After, WLK (Walking) 10.14% and FHP (Free-hand performing) 9.54%.

Table 7.21 – Data collected and classified as W4MP.

W4MP	Acron.	Process	Productive State	N. Observations	%
Free-hand performing	FHP	Operation	Productive or Direct work	111	9.54%
Auxiliary tools	AUT	Inspection	Contributory or Support work	28	2.41%
Manual tools	MNT	Operation	Productive or Direct work	215	18.47%
Electric/Electronic tools	EET	Operation	Productive or Direct work	10	0.86%
Machines operation	MOP	Operation	Productive or Direct work	228	19.59%
Robotic automation	RBA	Operation	Autonomous Production	0	0.00%
Do not operating value	IDL	Delay	Nonproduction work	376	32.30%
Walking	WLK	Delay	Nonproduction work	118	10.14%
Carrying	CAR	Transportation/ Storage	Contributory or Support work	78	6.70%

A low inspection rate is observed, as there is no great need for measurements during work. Since transport is mostly carried out by machines (operators), workers were mostly transporting their tools and accessories. The delay is primarily related to the time that other workers wait for the machines'

actions (e.g. excavation), and the acts of walking along the service fronts. Finally, operations represent the highest rate of activity. In the sequence, it presented the determined values:

- Operation: number of observations (564) 48.45%;
- Inspection: number of observations (28) 2.41%;
- Delay: number of observations (494) 42.44%;
- Transportation/ Storage: number of observations (78) 6.70%.

The Productive or Direct work is the equal proportional as the Labour Rating Factor, Equation (3), determining an LRF of 48.45% [91]. Based on Equation (4), it is determined that 50.73% for LRF-C (Labour Rating Factor plus Contributory Work) [91].

According to Adrian (2004), it can be measured based on a work-day that 48.45% is Productive, and 51.55% is Nonproductive [91]. That 48.45% proportion accounting the Equation (2) for statistic validation a sample required was of 1,152 observations (confidence level of 90% and accuracy of ±5%) been the limit of error of ±2.42% (5% of 48.45%) [160].

As the total observations were of 1,164, it can be stated that within the prescribed confidence level of 90% that is sure that the crew is productive somewhere between 50.88% and 46.03% of the time. Following the sum of the productive states:

- Productive or Direct work: number of observations (527) 48.45%;
- Contributory or Support work: number of observations (98) 9.11%;
- Nonproduction work: number of observations (461) 42.44%.

Finally, the W4MP Mechanization index, as stated on Equation (1) is the proportion of the three mechanized processes (EET - Electric/Electronic tools; MOP - Machines operation; RBA - Robotic automation) upon the Operation processes, without considering the other processes as Inspection, Delay, and Transportation/storage. And it can be classified in a scale as: Low (0% to 20%); Moderate (21% to 40%); High (41% to 60%); Very high (above 61%).

$$(M4MP)\ Mechanization\ index\ = \frac{EET+MOP+RBA}{\sum Operation\ Processes} \qquad (1)$$

As a result, the W4MP Mechanization index for that piping activity is 42.20% been considered as High in the scale proposed.

7.3.3 MASONRY (RESIDENTIAL BUILDING WITH EXPANDED CLAY BLOCKS)

Masonry tasks were monitored on a residential building project. In this, the internal partitions walls are built with blocks of expanded clay, and a silo supplies the prefabricated mortar. Only the brickwork was analysed (without coatings).

7.3.3.1 Data collection and Sample

Data was collected between 2020/6/19 and 2020/6/26 by two researchers. Part of this experiment will also be used in a master's thesis, which is co-supervised by the author and supervised by Professor Hipólito de Sousa. In average, two to four craft workers were observed at once point of view. The crew was composed of three masons and an assistant.

The activities basically correspond to laying individual masonry units (expanded clay blocks 400x190x200mm, 15kg) with horizontal and vertical joints in mortar. It is necessary to measure the plumb/level of the walls. As well as, there is a demand for support services such as the supply of mortar at the application sites, the cutting of some blocks into smaller pieces and the placement of a connecting frame between masonry and concrete elements.

Figure 7.51 shows the machines, tools, and accessories used in this worksite. A machine supplies the mortar on the floor where the work was carried out. Drill and grinder are the electric tools used by the craft workers. Different manual tools and accessories are used (e.g. trowel, float, shovel, hammer, wheelbarrow). Also, auxiliary tools are used to measure position and verticality (e.g. level tool, tape measure).



Figure 7.51 – Tools, machines and accessories.

As previously mentioned, the author and another researcher made observations of the workers' actions (researcher in detail Figure 7.52). The author provided workers with wearables devices and interacted with them during the days to perceive/document their opinions and feelings about the technology (Figure 7.53).



Figure 7.52 – Researcher making observations.



Figure 7.53 – Researcher providing the wearables and interviewing the craft workforce.

Figure 7.54 depicts a craft worker during his daily routine wearing the devices on his wrists and legs (in this case a device was worn on the outside of his trousers, and the other leg on the inside). Finally, in Figure 7.55, see two other craft workers using the devices while performing masonry activities.



Figure 7.54 – Craft worker on duty wearing the devices.



Figure 7.55 – Craft workers on duty wearing the devices.

7.3.3.2 Discussion and findings

For the observed period of five working days in this worksite, 198 square meters of masonry were carried out, undertaking 145 Man-hours. With this, they were achieving an income factor of 0.73 Man-hours/m2. Table 7.22 shows the classification based on the W4MP of the 3,484 observations made about the crew in the same period. They are then presented graphically and relating their proportion to the measured income factor (Figure 7.56).

It can be seen that the lowest proportion was the MOP - Machine operation (mortar pumping machine), not counting the Robotic automation not observed at all. Tanking into account the Equation (2) for statistic validation of the sample in that methodology the value of 2.87% indicates a sample needed of 52,000 observations (confidence level of 95% and accuracy of 5%). Because of this, it cannot be said that this sample represents the total masonry task performance population.

Given that two observers collected 3,848 observation points in one week, it would take approximately fifteen weeks for two researchers to reach the required 52,000 observations. As a result, considering the number of observations and the period, it is determined that at least each worker was observed by one of the researchers every three minutes, which is a high frequency, and it can be inferred that the results denote/represent to the workers' occupation/performance during the experiment time.

Table 7.22 – Data collected and classified as W4MP.

Worker 4.0	Acron.	Process	Productive State	N. Observations	%
Free-hand performing	FHP	Operation	Productive or Direct work	486	13.95%
Auxiliary tools	AUT	Inspection	Contributory or Support work	307	8.81%
Manual tools	MNT	Operation	Productive or Direct work	1378	39.55%
Electric/Electronic tools	EET	Operation	Productive or Direct work	247	7.09%
Machines operation	MOP	Operation	Productive or Direct work	100	2.87%
Robotic automation	RBA	Operation	Autonomous Production	0	0.00%
Do not operating value	IDL	Delay	Nonproduction work	288	8.27%
Walking	WLK	Delay	Nonproduction work	311	8.93%
Carrying	CAR	Transportation / Storage	Contributory or Support work	367	10.53%

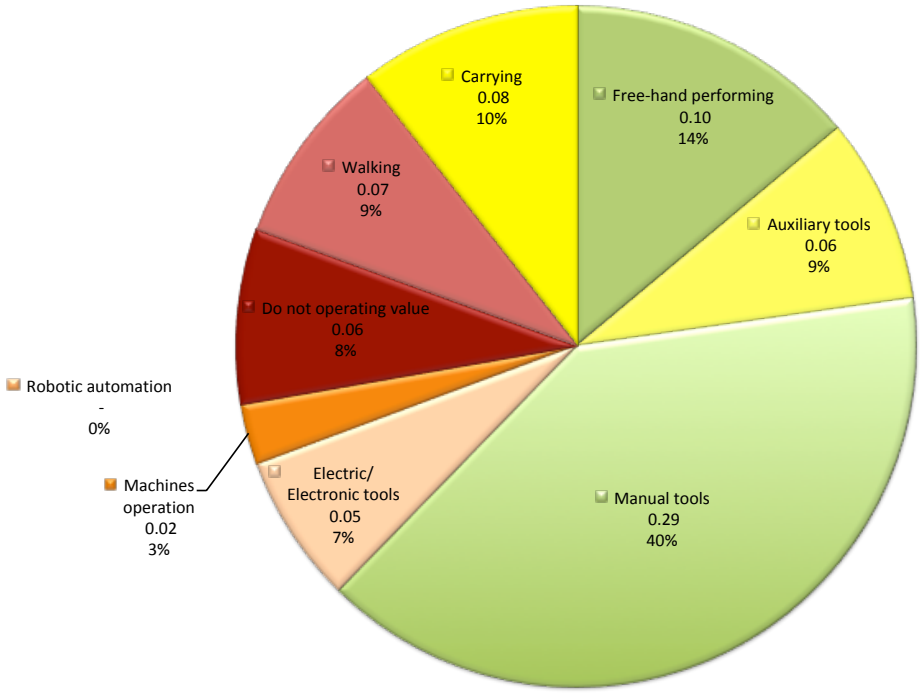


Figure 7.56 – W4MP Crew process classification.

Figure 7.57 presents the processes classification, and Figure 7.58, the assessed productive states. The modelling of this masonry process makes it possible to measure that most of the time (approximately 40%) the craft worker is handling a hand tool (mainly the trowel and the float with the action of laying mortar). In the sequence, the most systematic process is the free-hand performing (approximately 14%), which in most cases is the action of laying the blocks.

Approximately 64% of the time, workers are carrying out operations in a productive state. Most of the transports (loading) performed are the supply of mortar and blocks near the application sites. Inspection activities are carried out by the workers themselves to guarantee the plumb and level of the elements and the thickness of the vertical joints. It should be noted that the block has a system that contains the vertical joint between two blocks in contact (giving even the false impression that it does not exist).

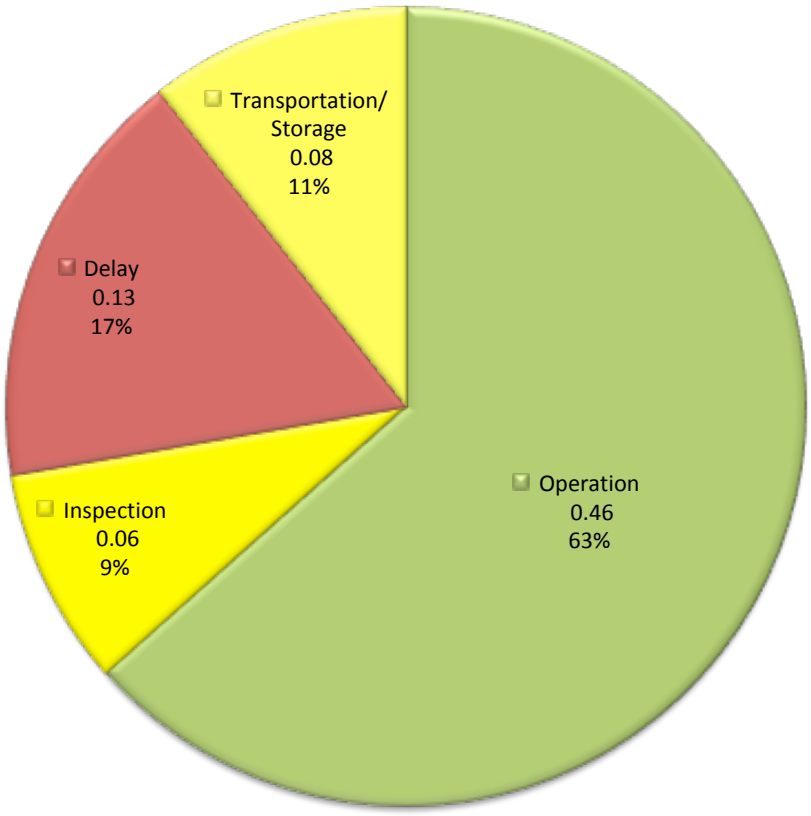


Figure 7.57 – Processes classification.

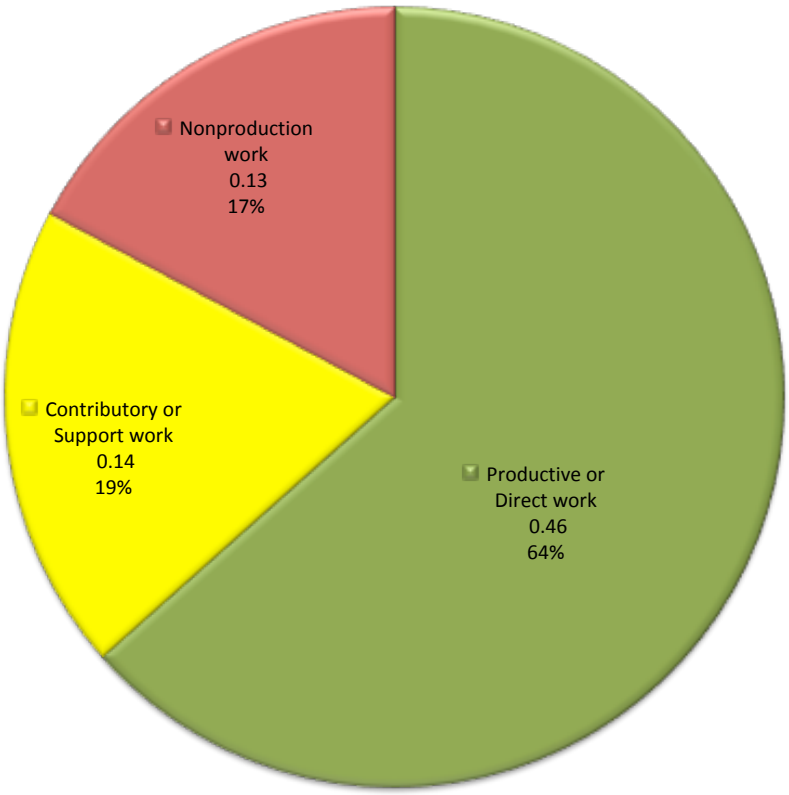


Figure 7.58 – Productive states classification.

The Productive or Direct work is the equal proportional as the Labour Rating Factor, Equation (3), determining an LRF of 63.46% [91]. Based on Equation (4), it is determined that 68.30% for LRF-C (Labour Rating Factor plus Contributory) [91]. According to Adrian (2004), it can be measured based on a work-day that 63.46% is Productive, and 36.54% is Nonproductive [91].

That 36.54% proportion accounting the Equation (2) for statistic validation a sample required was of 2,669 observations (confidence level of 95% and accuracy of ±5%) been the limit of error of ±1.83% (5% of 36.54%) [160]. As the total observations were of 3,484, it can be stated that within the prescribed confidence level of 95% that is sure that the crew is nonproductive somewhere between 34.71% and 38.37% of the time.

Finally, the W4MP Mechanization index, as stated on Equation (1) is the proportion of the three mechanized processes (EET - Electric/Electronic tools; MOP - Machines operation; RBA - Robotic automation) upon the Operation processes, without considering the other processes as Inspection, Delay, and Transportation/storage. And it can be classified in a scale as: Low (0% to 20%); Moderate (21% to 40%); High (41% to 60%); Very high (above 61%). As a result, the W4MP Mechanization index for that masonry activity is 15.69% considered Low in the scale proposed.

Modelling the masonry task on the Worker 4.0 Flow to boost Productivity highlights the influence of manual tools over the processes (Figure 7.59).

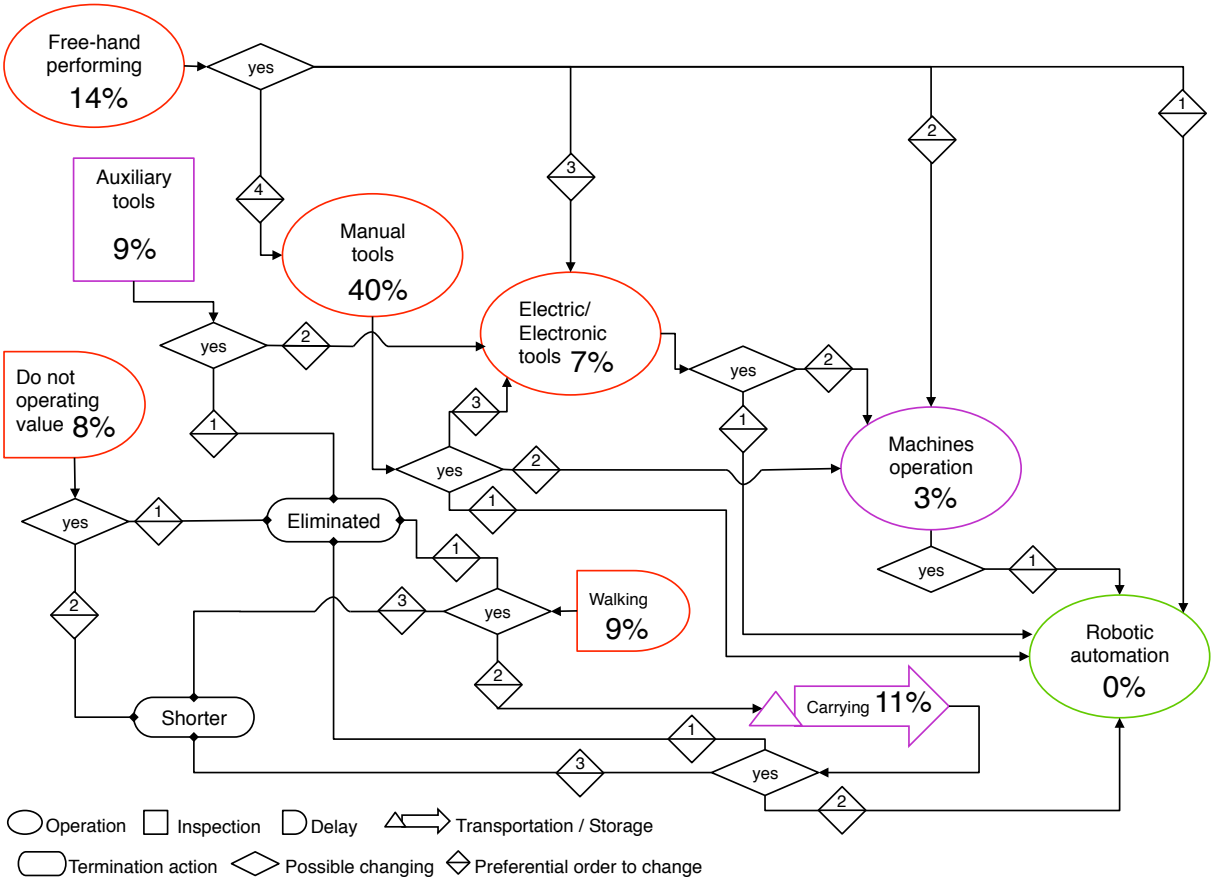
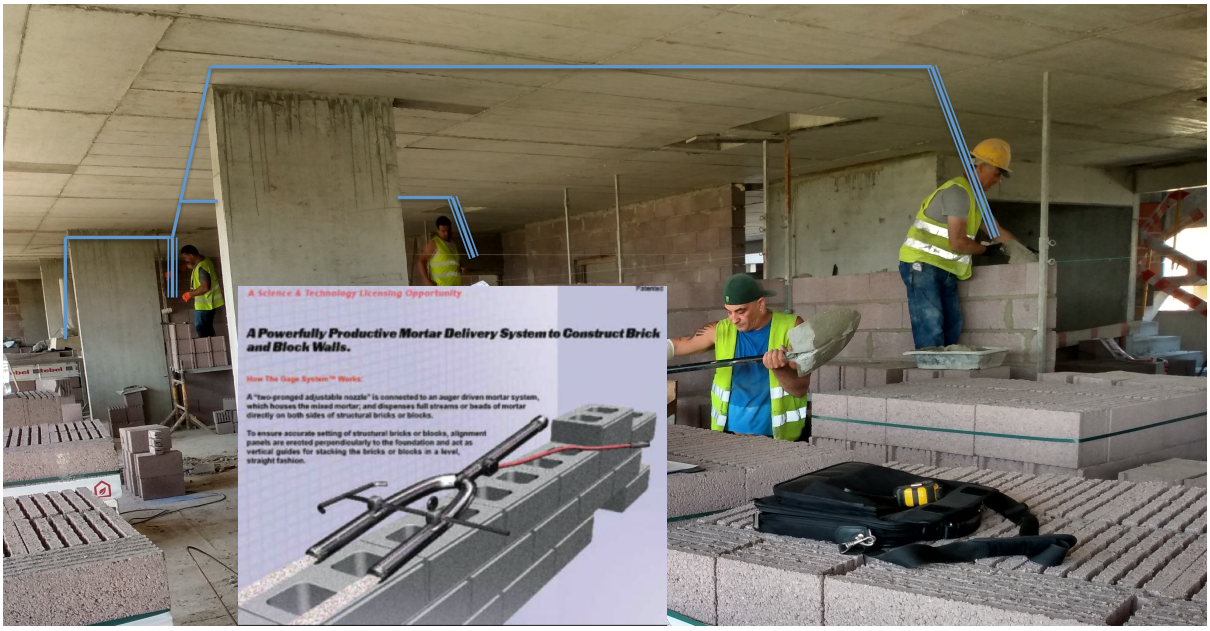


Figure 7.59 – W4MP modelled.

Based on the proposed "First analysis indications on how to boost efficiency and mechanization levels" on Chapter 6 above, it can be analysed the Manual tools process by the question:

- Does the activity justify the use of an electric/electronic tool or mechanized or automated robotic equipment?

Responding to this, the search for a mechanized process to dispense mortar is envisaged. Therefore it presents an innovative solution to solve this issue, as shown in Figure 7.60, adapted from an already patented solution [313].



"The Gage System™, a patented method of constructing a brick or block wall, features a mortar delivery device and a block alignment panel. The auger-driven delivery system forces mortar through an attached hose to a delivery nozzle. The nozzle is connected to a pressurized tank housing the mixed mortar, and the delivery device deposits mortar along the edges of a brick. The nozzle has two outlets that can be spaced apart to approximate the distance between the edges of bricks or blocks."
https://www.techbriefs.com/component/content/article/tb/pub/features/technologies/19409

Figure 7.60 – Mortar dispenser system (adapted from Gage System [313]).

7.3.3.2.1 Craft workers opinion/feelings

In order to avoid any identification of the thoughts/opinions of the interviewed workers, no correlation to their functions/names will be made. Some personal characteristics will be presented to illustrate the situation, however avoiding any direct reference.

The comfort/discomfort of using the wearables devices on the wrists and legs:

Two of the workers who already wore wristwatches indicated that they did not feel any discomfort when wearing the devices. In contrast, the other two workers who did not wear watches in their day-to-day reported discomfort when wearing it; one of them said that he would not use the devices because of this discomfort;

The workers expressed significant discomfort when filming their actions. Physical reactions of inhibition were observed. Furthermore, a worker demonstrated a verbal discontent with the footage, asking, "is it being posted live on the internet?".

The perspective of being monitored by academic purposes and future similar monitoring by the employer:

In general, the workers agreed to use the wearables for academic purposes. Only one of them after being monitored on the first day refused to continue using the devices and declined to speak for what reasons;

One of the workers indicated that he was already using "this type of equipment" because his smartphone was already monitoring his heartbeat by an app;

One of the workers indicated that he had already seen this type of monitoring in professional football players;

The workers, when faced with the idea of a future request/demand on the part of the employer to use the monitoring devices, were generally vague, not directly answering the question. Even when the possibility of financial compensation was indicated, the workers did not want to commit themselves to any affirmation/denial. Only one of the workers said that he would use the devices without any problem and that this would not influence him at all.

The data ownership:

The workers, in general, did not express a position regarding data ownership. Two of them expressed an interest in having access to the data for a self-assessment;

It can be observed that the lack of knowledge regarding electronic performance monitoring inhibits the formulation of a favourable/unfavourable position regarding the collected data.

The benefits/threats of using this type of monitoring technologies and the mechanization of work:

Two of the workers indicated monitoring health as a benefit. They stressed that the work requires a tremendous physical effort and that the control of expended calories and the fatigue would be relevant;

As with the example of football players, workers realized the importance of monitoring performance. However, they cannot see/measure any benefit for their own;

When indicated that these studies could better evaluate production processes, enhancing improvements, and increasing mechanization, one of the workers was effusively against any mechanization. In his words: "Mechanization is bad because it takes away our work. If there is more machine, we have less work, and that is bad.". Even when it was argued that the machines are to assist the worker (such as an electric drill), this same worker maintained his position contrary to mechanization, encouraging his colleagues to agree with this position;

Two opposite situations can be observed. The youngest worker in age and length of service (who knows more about technologies) was more interested in the subject of the research, at the same time, he felt more threatened by the work and even refused to continue developing the experiment. The most senior worker, in age and length of service (who also appears to have less knowledge of new technologies), does not feel at all threatened when using the devices, nor is he against the monitoring;

Quieter/less talkative workers tend to observe and follow the positions of more talkative workers, who tend to be the opinion leaders within the group.

Some significant social barriers experienced during the interviews should be highlighted. Firstly, the author used personal protective equipment throughout all the experiment, including a respiratory protection mask (for the reason of COVID-19). Due to the pandemic and social rules, a physical

distance between the author and the workers were maintained whenever possible. As seen in the figures, these workers do not use all PPE, nor do they wear masks (against dust inherent in activities, nor due to COVID-19).

Workers may have perceived these factors as a “barrier” and even fear of a proximity/interaction by the author. Besides, the author is a foreigner, not having the same jargon appropriate to approach/dialogue with the craft workers. However, these barriers may have hampered communication between the interviewer and the interviewees.

7.3.4 MASONRY (COMMERCAIL BUILDING WITH EXPANDED CLAY AND CONCRETE BLOCKS)

Masonry tasks were monitored on a commercial building project. In this, the internal partitions walls are built with blocks of expanded clay and also concrete. The prefabricated mortar was supplied every day and stored in cubic containers (0.5 m^3 approximated) as seen in Figure 7.61. Only the brickwork was analysed (without coatings).

7.3.4.1 Data collection and Sample

Data was collected between 2020/8/10 and 2020/9/14 by two researchers. As well as the before work, part of this experiment will also be used in a master's thesis. On average, two craft workers were observed at once point of view. The crew was composed of three masons and an assistant.

The activities correspond to laying individual masonry units (expanded clay blocks 400x190x200mm, 15kg, and concrete blocks 500x200x200mm, 14.6kg) with horizontal and vertical joints in mortar. In this project, the wall panels have big dimensions 7 meters high and 7.5 meters long, see Figure 7.62.

It is necessary to measure the plumb/level of the walls. As well as, there is a demand for support services such as the supply of mortar and blocks at the application sites. Also, the wall execution tasks demanded to cut some blocks into smaller pieces.

A forklift supplies the mortar and the blocks on the scaffolding elevation where the work was carried out, as presented in Figure 7.63. Drill and grinder are the electric tools used by the craft workers. Different manual tools and accessories are used (e.g. trowel, float, shovel, hammer, wheelbarrow). Also, auxiliary tools are used to measure position and verticality (e.g. level tool, tape measure).



Figure 7.61 – Prefabricated mortar.



Figure 7.62 – Wall panels.



Figure 7.63 – Forklift filling products at elevations.

As previously mentioned, the author and another researcher made observations of the workers' actions. Also, the author provided workers with wearables devices and interacted with them during one day to perceive/document their opinions and feelings about the technology (Figure 7.64).



Figure 7.64 – Researcher providing the wearables and interviewing the craft workforce.

7.3.4.2 Discussion and findings

During five working days in this worksite, 242 square meters of masonry were carried out, undertaking 158 Man-hours. With this, they were achieving an income factor of 0.65 Man-hours/m2. Table 7.23 shows the classification based on the W4MP of the 3,606 observations made about the crew in the same period. They are then presented graphically and relating their proportion to the measured income factor (Figure 7.65).

It can be seen that the lowest proportion was the AUT - Auxiliar tools, not counting the Robotic automation not observed at all. Tanking into account the Equation (2) for statistic validation of the sample in that methodology the value of 3.85% indicates a sample needed of 38,879 observations (confidence level of 95% and accuracy of 5%). Because of this, it cannot be said that this sample represents the total masonry task performance population. Given that two observers collected 3,606 observation points in one week, it would take approximately eleven weeks for two researchers to reach the required statistical number of observations. Considering the number of observations and the period (workday with ten hours long), that represents that at least each worker was observed by one of the researchers every six minutes, which is a high frequency, and it can be inferred that the results denote/represent to the workers' occupation/performance during the experiment time.

Table 7.23 – Data collected and classified as W4MP.

Worker 4.0	Acron.	Process	Productive State	N. Observations	%
Free-hand performing	FHP	Operation	Productive or Direct work	734	20.35%
Auxiliary tools	AUT	Inspection	Contributory or Support work	139	3.85%
Manual tools	MNT	Operation	Productive or Direct work	1488	41.26%
Electric/Electronic tools	EET	Operation	Productive or Direct work	153	4.24%
Machines operation	MOP	Operation	Productive or Direct work	198	5.49%
Robotic automation	RBA	Operation	Autonomous Production	0	0.00%
Do not operating value	IDL	Delay	Nonproduction work	278	7.71%
Walking	WLK	Delay	Nonproduction work	426	11.81%
Carrying	CAR	Transportation / Storage	Contributory or Support work	190	5.27%

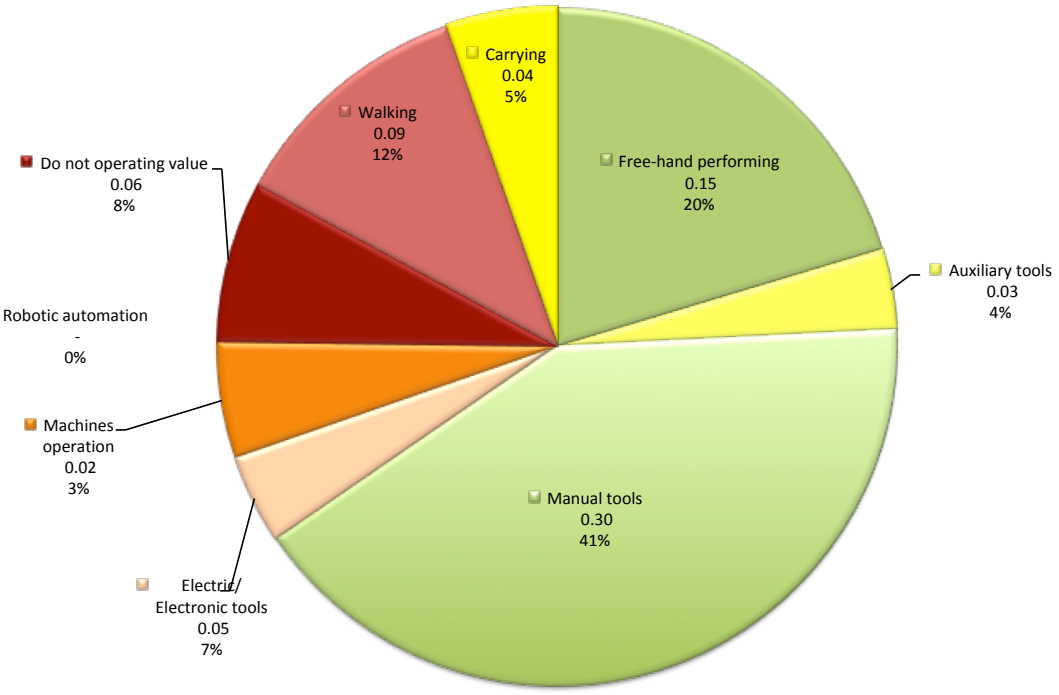


Figure 7.65 – W4MP Crew process classification.

Figure 7.66 presents the processes classification, as well, Figure 7.67 presents the productive states measured. The modelling of this masonry process makes it possible to measure that most of the time (approximately 41%) the craft worker is handling a hand tool (mainly the trowel and the float with the action of laying mortar). That result is very similar confronting the 40% achieved in the residential masonry project presented in the previous section.

In the sequence, the most systematic process is the free-hand performing (approximately 20%), which in most cases is the action of laying the blocks. That action was also the second action most measured in the other masonry tasks observed, a comparison between the three experiments will be detailly discussed in the next 7.3.5 Section.

Approximately 71% of the time, workers are carrying out operations in a productive state. As 20% of workers occupation is connected to a nonproduction state and 9% doing some contributory or supportive work.

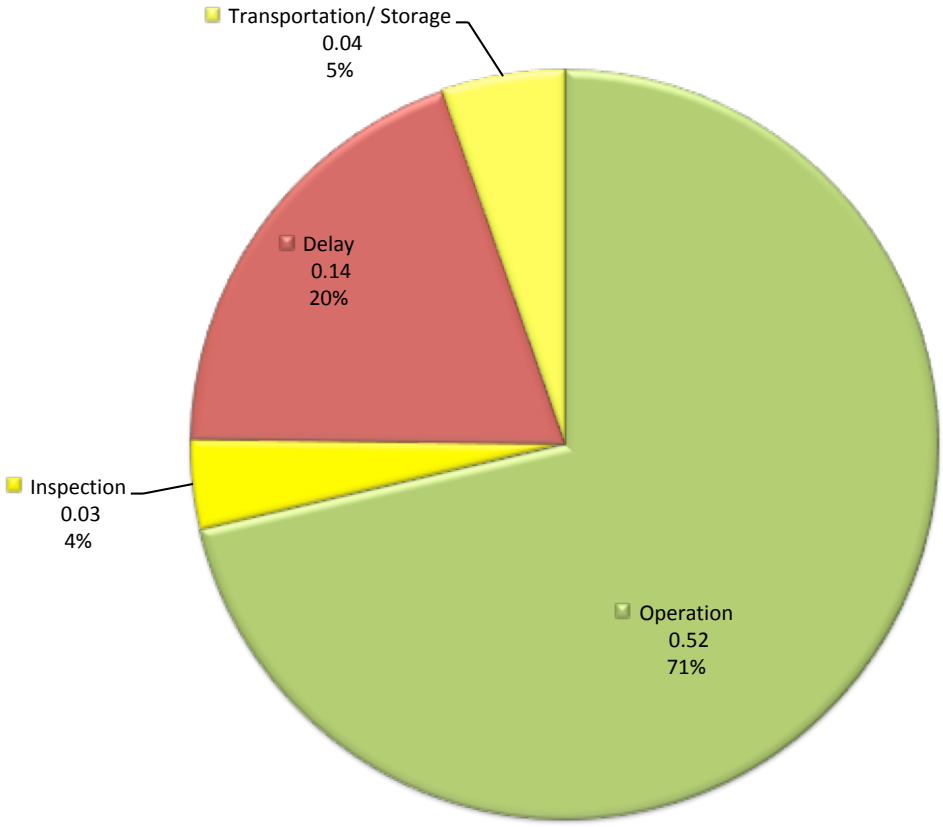


Figure 7.66 – Processes classification.

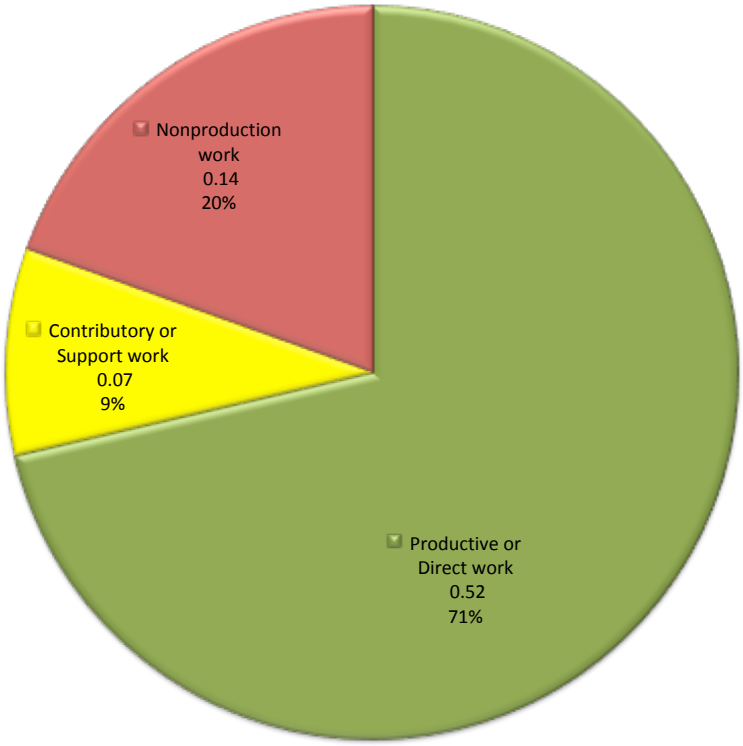


Figure 7.67 – Productive states classification.

The Productive or Direct work is the equal proportional as the Labour Rating Factor, Equation (3), determining an LRF of 71.35% [91]. Based on Equation (4), it is determined that 73.63% for LRF-C (Labour Rating Factor plus Contributory) [91]. Also, according to Adrian (2004), it can be measured based on a work-day that 71.35% is Productive, and 28.65% is Nonproductive [91].

That 28.65% proportion accounting the Equation (2) for statistic validation a sample required was of 2,696 observations (confidence level of 90% and accuracy of ±5%) been the limit of error of ±1.43% (5% of 28.65%) [160]. As the total observations were of 3,606, it can be stated that within the prescribed confidence level of 90% that is sure that the crew is nonproductive somewhere between 27.21% and 30.08% of the time.

Finally, the W4MP Mechanization index, as stated on Equation (1) is the proportion of the three mechanized processes (EET - Electric/Electronic tools; MOP - Machines operation; RBA - Robotic automation) upon the Operation processes, without considering the other processes as Inspection, Delay, and Transportation/storage. And it can be classified in a scale as: Low (0% to 20%); Moderate (21% to 40%); High (41% to 60%); Very high (above 61%). As a result, the W4MP Mechanization index for that masonry activity is 13.64% considered Low in the scale proposed.

As determined the level of mechanization between masonry activities is approximate, both being classified as low. Which results is not surprising given the high rate of manual work required for this process. Simultaneously, piping activity reached a higher mechanization level than masonry activities, which was also expected given the mechanical excavations inherent in that piping tasks. Forward the results of the three experiments will be confronted and discussed.

Finally, Figure 7.68 presents the masonry task's modelling on the Worker 4.0 Flow to boost productivity, highlighting the influence of manual tools and free-hand performing over this process. Firstly, in the search for the highest possible productivity, fully robotic work will be the first choice. However, automated masonry processes are not yet available on the market, mainly because they do not reach an appropriate cost-benefit ratio.

Then, alternatives will be sought to increase this production process with machines. As an example, Ryu et al. (2020) experienced a self-levelling pallet (machine) to have the bricks/blocks to the level of workers' hands, decreasing the need for that free-hand motion of collect the product at a lower level [314]. This experiment shows that self-levelling pallet can prevent postural diseases and provide productivity improvement [314]. Figure 7.69 extract from Ryu et al. (2020) illustrates the solution tested [314]. The purpose of the Worker 4.0 Flow is that by modelling the worker/crew activities quantitatively, a prone tool to indicate a path to boost productivity will be provided.

Most important, in the case of the experiment made by Ryu et al. (2020) [314], if the designed flow wore applied it would be possible to measure how the introduction of that machine changed the process. The cycling approach indicated in this work highlights that adequated best practice after implementing a process improvement action is to conduct their assessment. This evaluation can lead to the mapping of the best process designs, providing benchmarketing, indicating other improvement factors on the tasks' process, not only evaluating the number/quantity of outputs produced.

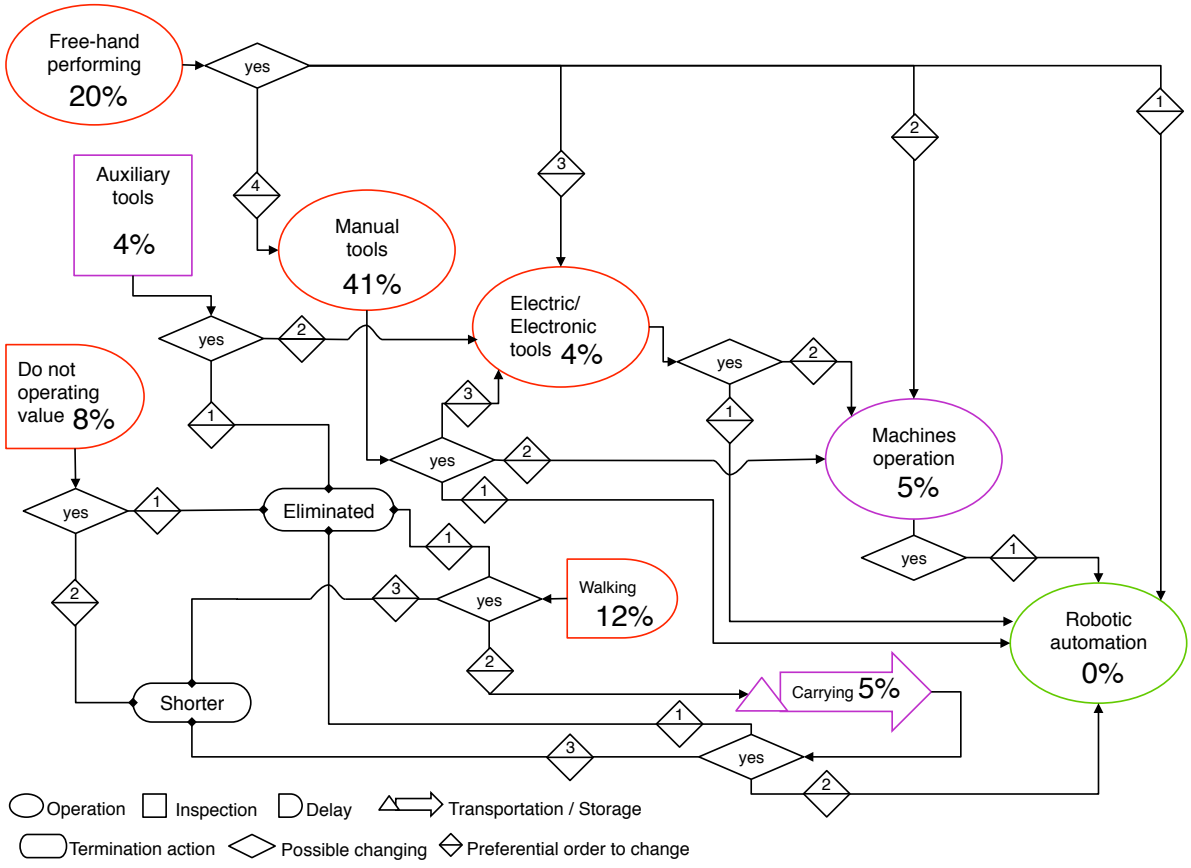


Figure 7.68 – W4MP modelled.



Figure 7.69 – Self-leveling pallet tested by Ryu et al. (2020). [314]

7.3.4.2.1 Craft workers opinion/feelings

In order to avoid any identification of the thoughts/opinions of the interviewed workers, no correlation to their functions/names will be made. The masonry crew observed in these masonry tasks was a small subcontract enterprise. Where the owner of that company also worked together with the team as a mason. These peculiar characteristics generated less interaction between the researchers and the craft workers. That was observed that the owner lead the opinions and the other workers just manifested concordance.

The comfort/discomfort of using the wearables devices on the wrists and legs:

None of the workers expressed any discomfort when using wearable devices;

There was also no adverse reaction/perception regarding the filming of the workers' actions when they were wearing the devices.

The perspective of being monitored by academic purposes and future similar monitoring by the employer:

In general, the workers agreed to use the wearables for the academic purpose;

The workers, when faced with the idea of a future request/demand on the part of the employer to use the monitoring devices, were generally vague, not directly answering the question. Even when the possibility of financial compensation was indicated, the workers did not want to commit themselves to any affirmation/denial;

Only the worker who was also the team owner indicated that desire to have tools to measure productivity to boost performance.

The data ownership:

The workers, in general, did not express a position regarding data ownership. Again, just the team' owner expressed an interest in having access to the data;

It can be observed that the lack of knowledge regarding electronic performance monitoring inhibits the formulation of a favourable/unfavourable position regarding the collected data. The position of the other workers regarding the employer been part of the experiment could have inhibited honest feedback.

The benefits/threats of using this type of monitoring technologies and the mechanization of work:

As an example of the collection of the impressions above question, a similar situation of the other workers not delivering opinions and the owner been favourable of the mechanization of the work/tasks was detected.

However, in the context presented, it was clear that the employer's situation integrating the team of workers and sponsoring the experiment generated in the other workers a natural inhibition for them to send more sincere/opposite feedback. On the other hand, it can be seen that leadership sponsorship can positively influence EPM implementation effectiveness.

7.3.5 COMPARISON AND DISCUSSION OF THE RESULTS OF THE THREE DIFFERENT EXPERIMENTS

Figure 7.70 shows the results of the experiments given the nine processes recommended in W4MP. Between the two activities evaluated in masonry buildings (residential and commercial), there is a remarkable similarity in the teams of workers' practical actions. Realize that due to the characteristic of smaller wall panels, the residential building work has more activities related to quality control (using auxiliary tools). This factor also influences the greater use of power tools (for cutting half a block) in the building residential worksite project. The distant location of the blocks and the need for a manual supply of mortar in the areas of use in the building residential work also influence a higher index of identified carrying actions. On the other hand, in the building commercial worksite, the support of the forklift indicated a more significant operation of machines, as well as it was observed that the workers walked more (also going up and down the stairs of the accesses of the scaffolding).

It can be indicated that a better distribution of materials in building residential work can reduce the need for loading activities by approximately 3%. It is also observed that potentially auxiliary activities in masonry performance for the residential building work could be reduced from 9% to 6%. With this, an increase in free-hand performing activities in this worksite would be boosted, and there would be an even more similar distribution of workers' actions in the two projects observed.

The comparative analysis between different projects/works regarding the accomplishment of similar tasks allows an analysis of the processes and identifying characteristics that can be better adapted to enhance a production increase. Nevertheless, analysis of benchmarking processes can lead to measures to standardize the teams' activities and boost productivity improvement.

When different activities (e.g. masonry and piping) are compared, one can observe how different the production processes are. However, it is also observed that control limits can be established, indicating where the effort should be concentrated to achieve more outstanding production.

In the case of piping activities, the results clarify what was observed regarding the opportunities for improvement in the worker-machine work systems. In the case evaluated, many workers (around 5) expected mechanical excavation without performing other activities in parallel. The synchronization of the activities of workers and equipment could increase in this case an increase of approximately 24% in other productive actions.

Finally, after this specific assessment of workers' actions in the context of established processes, it is possible to aim for an improvement in productivity by favouring activities connected with the productive process and mitigating non-productive ones. A general target would be, for example, to reduce the occupation of workers by 5% between carrying, walking, and those that do not operate value. Thus increasing the productive activities in this same order of 5%.

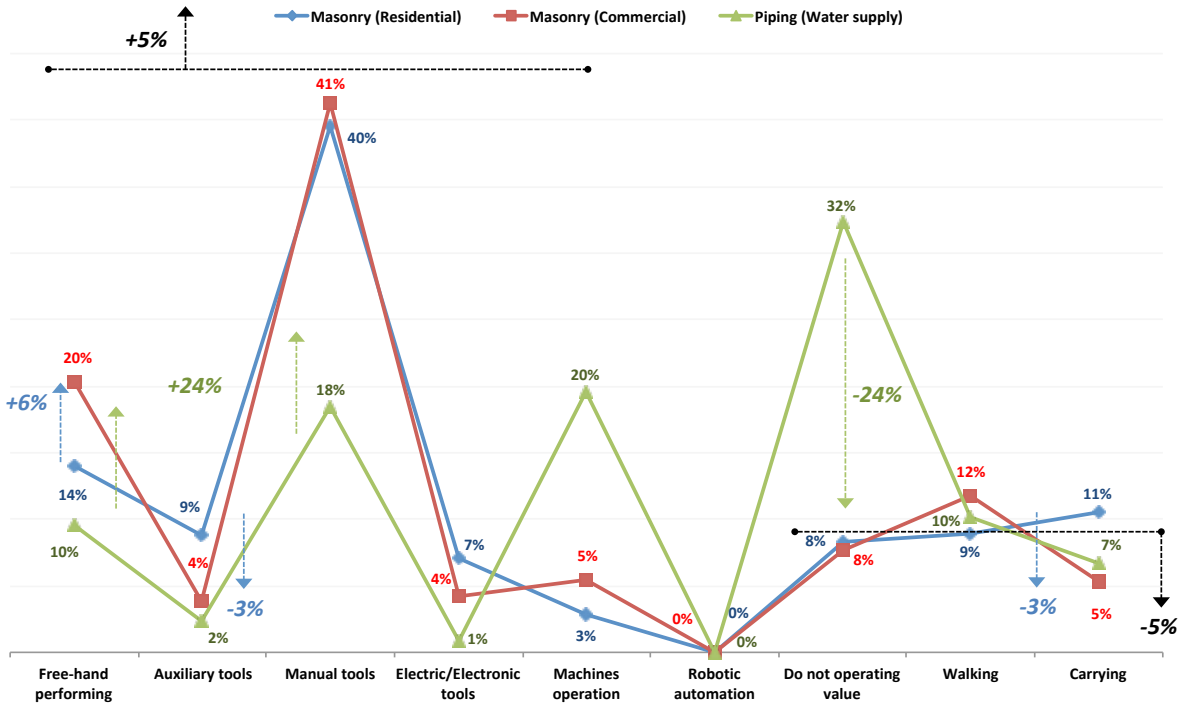


Figure 7.70 – W4MP Crew assessment.

Based on the same assumption of an increase in productivity previously diagnosed, there is a need to increase operating activities and decrease inspection actions (when possible). It is mandatory to reduce delays and transportation/storage actions (Figure 7.71). As seen in Figure 7.72, with an increase in direct work (productive), and decreasing in the contributory (support work), and most importantly, in the search for the elimination of non-productive work, high productivity can be achieved. Finally, that process alignment and balancing would increase the Labour Rating Factor of workers and crews potential boosting the task outcome rates (Figure 7.73).

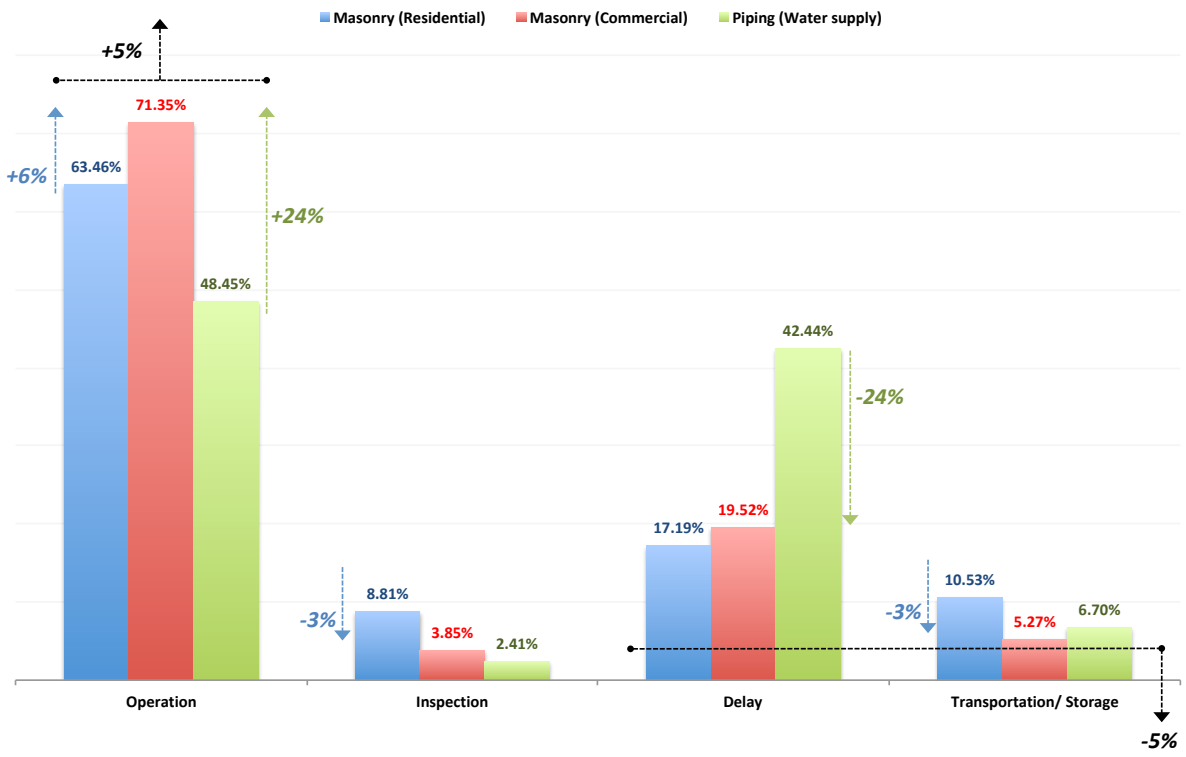


Figure 7.71 – Processess assessment.

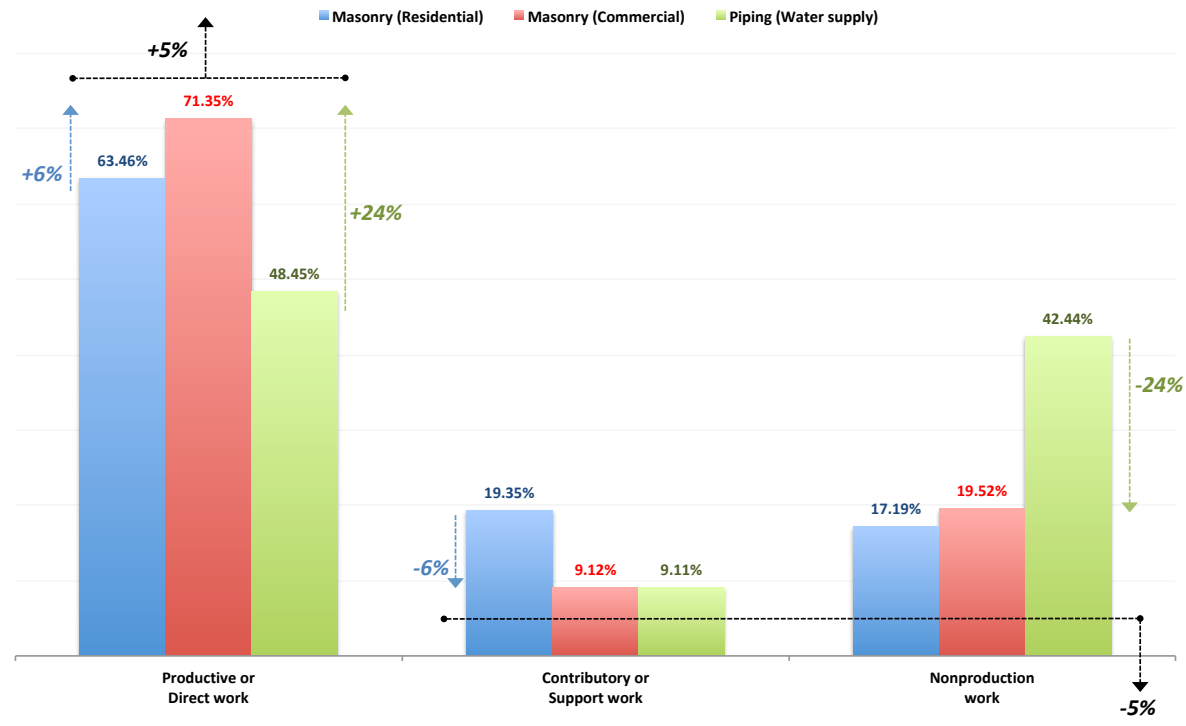


Figure 7.72 – Productive states assessment.

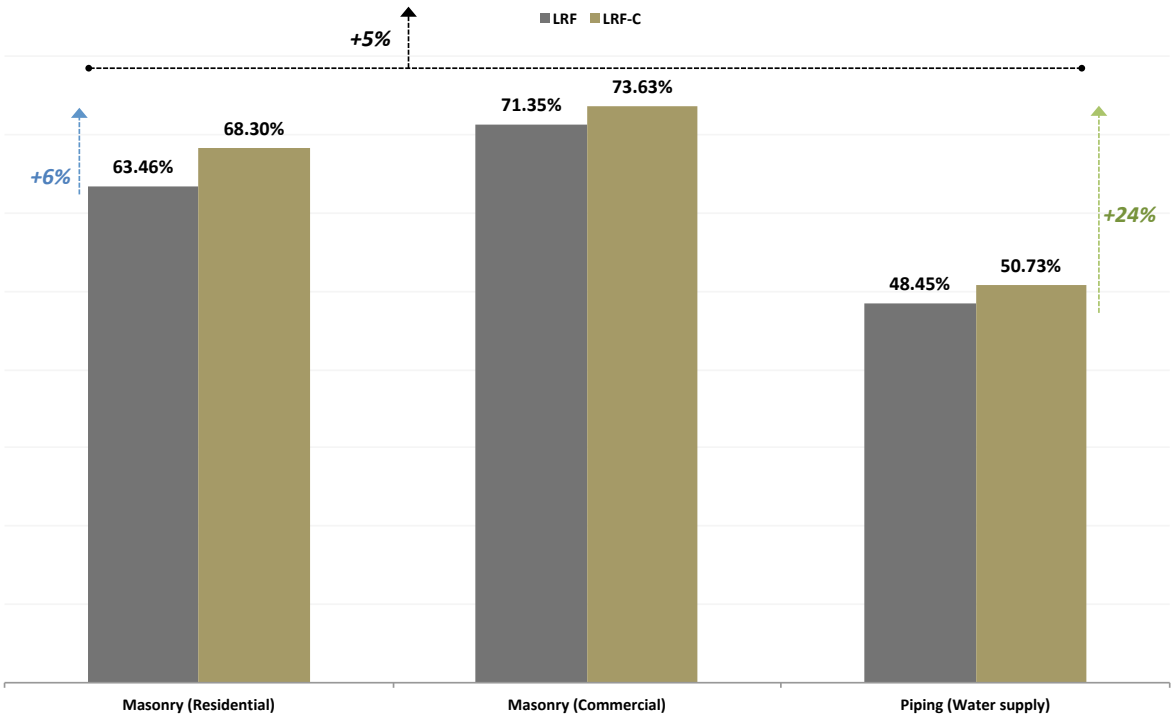


Figure 7.73 – Labour Rating Factor assessment.

Figure 7.74 shows the results of the mechanization level of the three evaluated tasks. As mentioned above, it is observed that each task achieved an expected mechanization index based on their particular characteristics. Significantly, it was measured that although the piping task has a high mechanization index, its productivity index is lower than the masonry tasks. Consequently, it is manifest that an increase in the level of mechanization of tasks is not enough to obtain better productive results. As identified, having some equipment in operation, and several workers on delay (waiting for the equipment operation) negatively impacts the production process.

The modelling of production processes based on the teams' performance allows identifying how the performance of each individual contributes to the overall performance of tasks. Thus, the distortions related to the interrelationship of activities and the lack of synchrony between workers-workers, workers-machine, and even workers and other actors (e.g. inspectors, supervisors) can be assessed. For example, the modelling of that piping task allowed a close view of that work-machine process, making explicit a process failure. Finally, the modelling of workers and teams' activities provides a greater level of knowledge about the production processes, indicating a more positive path for continuous improvement actions.

In the proposed W4MP (Worker 4.0 Motion Productivity), the mechanization level assessment is integrated into the task's modelling developed by the connected on-site crew. As a result, the evaluation of the mechanization level is made taking into account the work system and how the full process may be improved to achieve the best outcomes results.

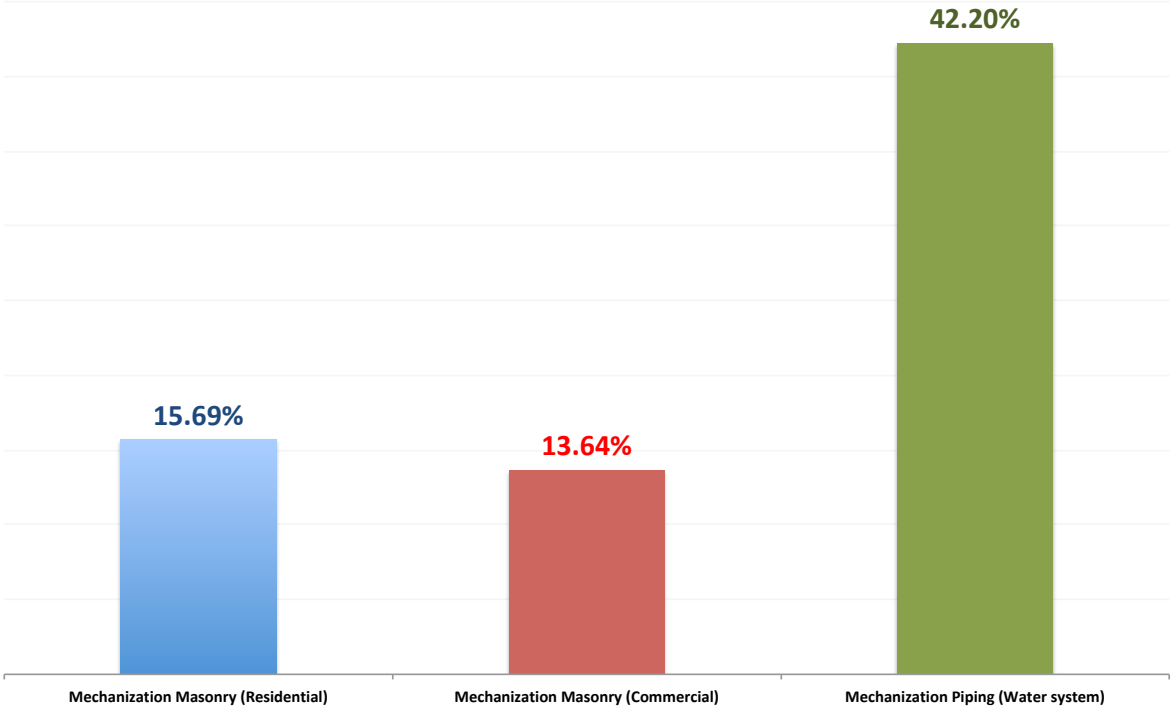


Figure 7.74 – Mechanization level assesment.

7.4 CHAPTER CRITICAL REVIEW

As a result, the on-site experiments made it possible to supply/test the proposed flows, demonstrating the potential of process modelling to evaluate productivity in the construction industry. It was also essential to collect the feelings/reactions of craft workers regarding EPM. Due to the global pandemic (Covid-19), the intended data collection and analysis processes were not possible; however, the mix of experiments conducted substantiated the proposed work. The concepts presented in the dimension of worker 4.0 allow the modelling of CI work systems and enhance productivity improvement. Data collection performed electronically, and its processing through artificial intelligence is very accurate and potent tools to scale-up the Worker 4.0 method within CI. Finally, the next chapter presents the conclusions and future directions of this work.

8
CONCLUSIONS

8.1 MAIN CONCLUSIONS

The answers to the questions formulated at the beginning of the investigation were presented throughout the work and briefly stood out: "What are the productivity concept, and how to assess it in the CI? What are the existing methods to measure and manage work systems? What are the most appropriate dimensions/levels to evaluate and improve productivity?". In Chapter 2, the literature review sought to identify the state-of-the-art regarding productivity in the CI and answer the three questions above. It was found that CI has a vision focused on projects and usually evaluates the performance of work at the task level, mainly evaluating/measuring inputs and outputs. It was found that possibility of 8 different levels for productivity assessment (Country, Industry, Project, Tasks, Work Elements, Basic Motion Elements). A gap was identified in the CI in terms of process modelling specific in the dimension of the Work Elements and the Basic Motion Elements. Finally, having it shown that the craft workforce is the primary source of on-site tasks development. It is clear that the evaluation of work in the dimension of the task-development processes and workforce-centred can lead to significant improvements in projects' results.

Before proceeding with the research, it was essential to check the feasibility of applying EPM; based on that in Chapter 3, it was responded: "What are the legal and ethical aspects regarding electronic data collection from construction workers? What are the impressions about EPM at managers' levels?". Before moving towards approaching craft workers, it was also idealised to identify what the management-level thought about EPM. This is because it will be the managers who will facilitate the implementation of the EPM and be the ones who will manage these systems and who will have to use the information for decision making. However, it was found that it is possible to implement EPM in compliance with GDPR. It is necessary that agents and local authorities regulate the application of EPM through collective labour agreements and that a series of authorisations/agreements be expressed based on transparent information. Consequently, were identified 18 packages of GDPR Agreements. Finally, based on the survey, an expressive level of 56% EPM acceptance was determined, and surprisingly 69% of the respondents first knew about EPM through the survey. This all demonstrates that more research and dissemination of these EPM-based methodologies are needed to achieve greater awareness.

To answer: "How to share on-site' information with stakeholders by different systems? What are the key performance indicators in construction project management?" in Chapter 4, it was studied what the "paths" of information would be in terms of systems and methodologies of processing/analysis that the data that is intended to collect on-site should go through. It also sought to identify the main KPIs that could be supplied with information from the EPM: Units per Man-Hours (input per output); Value associated per Units (input per output); On-time completion and time variation; Human resource management; Quality control and rework; Percent complete and speed of construction; Earned Man-Hours and values; Lost time accounting and identification; Punch list and Extra time; Safety (accident and hazard rates); Absenteeism; Motivation; Environmental Emissions. A flow of data/information was conceptualized and validated in interviews with Experts where the challenges for implementing EPM and the use of this information to manage human resources were pointed out. This flow starts

with implementing EPM on-site, passing through the interconnection of data with existing structures, notably BIM, passing through the data processing by AI, which would still allow the implementation of a management taking system. The possibility of using Blockchain was also indicated as a means of sharing/validating information between different stakeholders (aiming to increase the transparency of processes). Finally, all these processes were previously covered in the analysis of the GDPR compliance.

EPM state-of-the-art was identified in Chapter 5, responding to the question: "What is the state-of-the-art on electronic performance monitoring?". Based on the literature review, it was decided to select the wearable devices for further study and validation of the motion management study conceptualised in the developed framework. Chapters 2, 3, 4 and 5 connected delivered the target objectives of: "Provide in-depth knowledge to enable GDPR compliance; and, Conceptualise the EPM data flow, connecting system/methodologies.". The objective of "Conceptualise an approach to assess and modelling craft workforce productivity" was delivered in Chapter 6, where it was presented:

- Worker 4.0 Motion Productivity (Contenting nine processes: Free-hand performing, Auxiliary tools, Manual tools Electric/Electronic tools, Machines operation, Robotic automation, Do not operating value, Walking, Carrying);
- Worker 4.0 Flow to boost Productivity (Efficiency flow connecting the nine processes and accounting for the amount of performance on each; plus a Mechanization index level calculated based on the process modelling);
- Worker 4.0 Mapping chart (Two-hand methodology to be fulfilled based on an EPM system).

Finally, to achieve the objective of "Testing the EPM application and validation of the proposed framework", laboratory EPM simulation and on-site data collection were performed and presented in Chapter 7. The results applying EPM in a laboratory circuit performed by six volunteers by three clusters of tasks activities were:

- "Free-hand performing" activity (Masonry) plus two "Manual tools" processes (Painting and Roughcasting) for three IMUs (both wrists and one at the dominant leg) 92.71% accuracy for Machine-learning processing and 60.09% for Multivariate statistical analysis approach. And, for one IMU (only wrist-dominant data), 32.50% accuracy for Multivariate statistical analysis approach;
- "Manual tools" (Hammering, Sawing and Screwing) for three IMUs (both wrists and one at the dominant leg) 96.07% accuracy for Machine-learning processing and 76.07% for Multivariate statistical analysis approach. And, for one IMU (only wrist-dominant data), 76.23% accuracy for Multivariate statistical analysis approach;
- "Do not operating value" (Wearing PPE; Sitting; Standing still) and "Walking" (Walking) for three IMUs (both wrists and one at the dominant leg) 94.66% accuracy for Machine-learning processing and 47.41% for Multivariate statistical analysis approach. And, for one IMU (only wrist-dominant data), 46.60% accuracy for the Multivariate statistical analysis approach.

On-site experiments collecting data from three activities were performed, resulting in the modelling of the processes and fulfilling the Worker 4.0 Flow to boost Productivity, achieving:

- Water supply system (to consumers' taps) a Mechanization index of 42.20% considered High in the scale proposed.
- Masonry (residential building with expanded clay blocks) a Mechanization index of 15.69% considered Low in the scale proposed.

- Masonry (commercial building with expanded clay blocks and concrete blocks) a Mechanization index of 13.64% considered Low in the scale proposed.

The thesis main aim that was to develop a framework to measure craft workforce productivity, was delivered and partially validated. Due to the restrictions imposed by the world pandemic of COVID-19, it was impossible to carry out further experiments. Such restrictions limited the development of the work. In the electronic monitoring field, only was possible experiment ten activities that were catalogued among four of the nine idealized processes. It was also not possible to process data collected on-site electronically. To meet the need for process modelling, it was only possible to develop analyses at three different construction sites using a work sampling methodology. As a result, the amount of data/results was only limited to masonry and piping activities. It was impossible to perform any tests to validate the Worker 4.0 Mapping chart concept, nor was it possible to supply any KPIs identified with collected data.

The contribution to knowledge for theoretical implication includes the conceptualisation of a framework craft-workforce-centred focusing on the modelling of construction activities. The practical use of a quantitative Mechanization index can lead to a benchmarking of activities that are prone to delivery highest levels of outcomes and increase CI productivity. The future direction of this work should focus on expanding on-site data collection. It should also seek to establish algorithms for automating data processing.

8.2 OVERALL IMPLICATIONS

Increasing productivity in the construction industry is a complex objective. This work seeks to propose and test solutions that can contribute to this objective today and beyond. In this practical case, the on-site use of technologies is an equation with two primary factors. The costs of these innovations and the acceptance of their application by craft workers. The study tests hardware variations that use fewer sensors and also assess the number of sensors required to obtain satisfactory results. As important as, the innovative methodologies proposed potential benefits for the employers. Finally, several social and legal factors are evaluated to enable the implementation of electronic performance monitoring.

It is important to note that, a large number of human observations are necessary to validate the analysis statistically makes its execution very difficult, since the construction industry is based on projects with a beginning-end and not on processes continued as manufacturing. This particularity of the construction sector reinforces the usefulness of EPM methods for the collection of data related to productivity. Worker 4.0® is the concept that materializes the main principles and behaviour of workers in a Construction 4.0 scenario [315]. The Craft-workforce-centred concept is illustrated in Figure 8.1.

Precisely because the Worker 4.0 Motion Productivity is designed for the control and continuous improvement of processes that the four-step management method PDCA is properly to conduct that. First, it must be planning the innovation project based on Worker 4.0 Motion Productivity methodologies that are Craft-workforce-centred. Second, it is needed to do the data collection and processing. Next, check the performance of the processes assessing the level of mechanization. Finally, to act on on-site productivity, implementing actions to control and continuous improvement.

The work developed led to the systematization of a framework to standardize electronic productivity metrics. This framework becomes possible through a streamlined selection and definition of

performance indicators based on the main applications, metrics, and type of devices. This has direct implication with the characteristics of the works to be developed, the site conditions, as well as the type of organization and willing of the workers. The framework definition also brings a streamlined awareness of other essential aspects like legal, ethical and data security issues. The integration of workforce-related data on BIM and the implementation of Smart contracts foster all the concerns as mentioned earlier as well as traceability, collaboration, and transparency, enhancing projects efficiency.

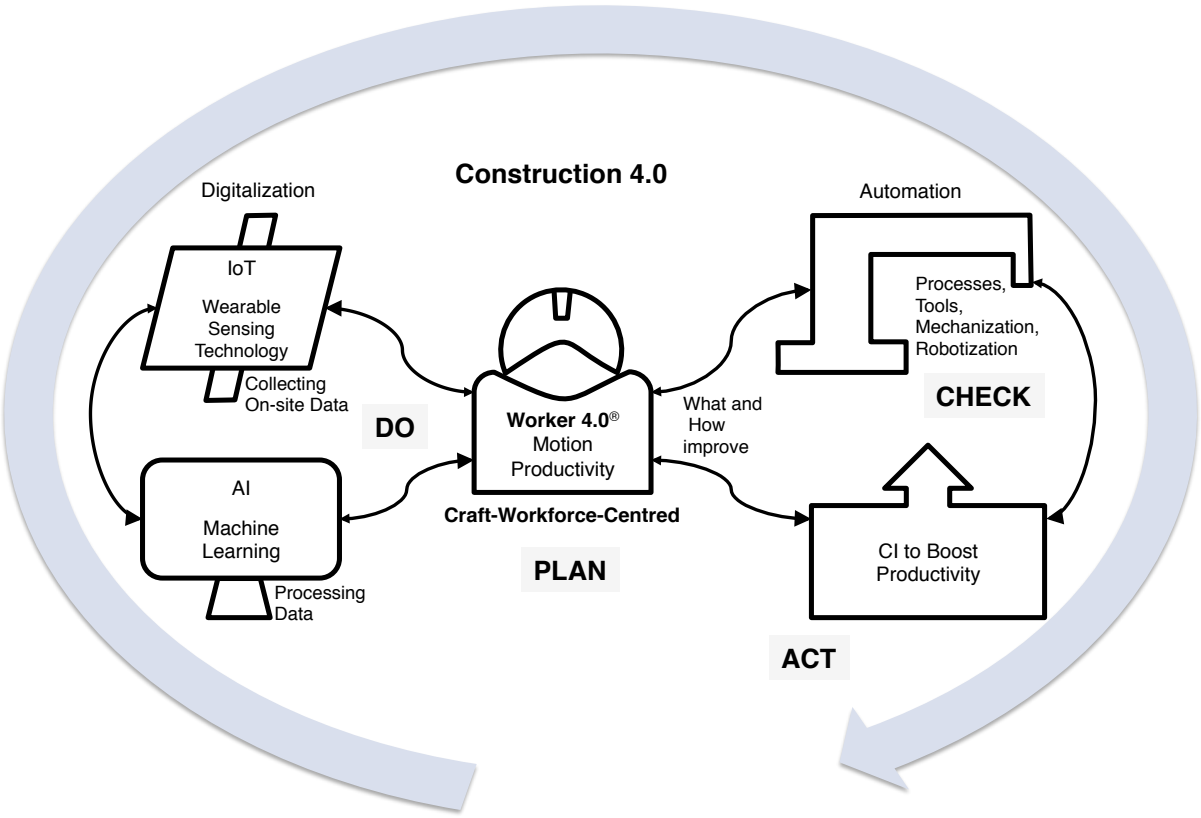


Figure 8.1 – Worker 4.0: Craft-workforce-centred.

As for data processing, machine-learning has reached relatively high levels of accuracy. However, the high demand for computational capacity and the need to carry out training sets of the algorithms with many features are factors that limit the rapid processing of information. Another negative aspect is the need to pre-label all data (in this case, frame-by-frame actions). Such labelling leads to tremendous and detailed manual work. When the multivariate analysis was performed with fewer features and less computational demand, faster results were obtained, but with less accuracy. Both cases require prior labelling, which requires a full video of the experiments. Such integral filming is easily achieved in a simulation environment (in this case, the many activities carried out in the laboratory). However, obtaining uninterrupted footage on the construction site is an almost impossible challenge. Firstly, there are the natural barriers of an active construction site, like other workers, equipment and especially the worker's dynamics and the physical space, which demands a large number of filming equipment. As a lesson learned and future recommendation, two key actions are indicated:

- Conduct experiments in controlled environments preliminarily and develop algorithms to test and improve these algorithms in the work environment;
- Use more than one analysis process, such as performing the labelling of activities through an automated analysis of the images and then applying AI to obtain faster outputs. Test new AI models that do not require the algorithms' training sets to search for results with the same accuracy and greater agility.

The research highlights the relevance of the GDPR as a policy tool to control methodologies and additional regulations defined at national or sector levels. Nevertheless, all should be able to allow the implementation of new technologies. Finally, and most importantly, it all leads to people's human agents of construction in this context. People are foundational in all industries, and resistance to change is a natural issue to deal with. Information, training and trust or confidence transmission are essential for the motivation and support of these agents. Facing such a dense framework for the purpose of the craft workforce and the successful implementation of EPM it is worthy of assuring a trusty environment at technology developers, employers, employees and regulators (policymakers) levels and all contractual agreements or rules that guide these relations.

Craft-workforce-centred construction productivity transformation is possible by inspiring people on-site to embrace 4.0 innovations. The challenge of increasing productivity will be achieved by making the tasks processes easier, effort-soft, more autonomous and implementing technology to measure performance.

8.3 FUTURE RESEARCH DIRECTIONS

8.3.1 OUTCOMES

Since the advent of industrial labour and mechanised production (1.0 industrial revolution) and passing through the introduction of mass-production and assembly lines (2.0 industrial revolution), the workers' performance has been monitored in order to improve production. The digitalization of the 3.0 industrial revolution introduced technologies on the companies' production, allowing new data processing methods. The 4.0 revolution brings the IoT to embed products, equipment, and people.

Products and services opportunities from Construction 4.0 in the spectrum of the craft workforce management include support by embedded sensors to the collection of data that allows near real-time monitoring. Following the data collection, post-processing using AI-management (for the purpose of e.g. recruiting, training, rewarding, punishment) and Smart Contract processes (for Information sharing, Monitoring Key Performance Indicators and project constraints, Contract automated execution) come in to broaden the impacts of EPM on the construction value-chain.

In the financial dimension, the challenges are linked with the investment requirements for developing technological solutions and the necessary increase of human resources related to the development and operation technological barriers must be overcome; safe and reliable systems designed without hidden bias. Human barriers such as that arising from an offensive strategy for ethical and moral use and data collection can cause bottleneck limiting the implementation of the technology. This can be avoided by streamlining the GDPR and collective agreements. Employers should take responsibility and have legitimate and transparent objectives, and employees must understand and trust the benefits and expressly consent to data collection and potential profiling. Preliminary agreements should regulate data ownership and ensure compliance with regulations. The analysis of existing regulation also shows

that there are gaps that require further research especially with regulation specific for the construction industry. Worker 4.0® is a brand registered in Portugal by the author [315]. Consultancy services are already offered/marketed to the construction industry by the brand Worker 4.0® see the website by the domains:

- worker40.info, and worker40.app
- mywork40.com
- mywork40mydata.com
- mywork4mydata.com
- prodyoup.com, prodyoup.eu and, prodyoup.app

These services consist of supporting companies for the development (start-up) of innovation projects to assess productivity. Based on the developed methodologies, monitoring sites/tasks and evaluating the productivity of small crews are possible as well, it provides a demonstration of feasibility for customers.

Throughout the Ph.D., investments were made. For the development of future new products, cost estimates, and consultation with suppliers were carried out, see detail below. The idealized products are based on the cloud service, with a web platform in IoT. The data from different wearable devices are collected and concentrated in an application and are viewed by a dashboard on the web or even in the app itself. There is also the possibility of developing proprietary wearable hardware with an estimated selling price of 130 euros each (for orders of 1,000 units).

- Investment made by the Author: € 137,400;
- Investment made by the FEUP: € 15,720;
- IoT: € 23,070;
- Dashboard and app: € 239,850;
- Back-end € 250,000;
- Hardware (design and prototype) € 98,400;
- Project management and administrative infrastructure € 239,200.

Worker 4.0 is a conceptualised methodology for workers connected to IoT based on the collection, integration, transmission, analysis, and storage of data related to performance. A new reality that presents itself today is that knowledge is increasingly acquired through digital means, the connection of the human with technology has already altered the ways of learning. In the Internet of Everything concept, the data for decision-making is delivered through devices by the most efficient process to the user.

Mobile applications that focus on work activities are currently corporate tools, more focused on processes and projects, not on each individual's activities. Both employers and employees are interested in applying tools to monitor job performance. However, the top-down approach to the insertion of the technology hinders its acceptance by the workers.

Individuals, especially Millennials, are already using devices widely to carry out their own tracking and guidance. Millennials are predisposed to passive monitoring and are also interested in a proactive experience of utilisation, and recommendations.

It is observed that the motivation common to all is the pursuit of personal improvement be it in terms of health, physical conditioning or sports practices. Furthermore, there is an opportunity in a segment

almost only exploited by corporations, relative to labour activities, both for self-employed workers and those within the competitive corporate world.

Worker 4.0 focusing the craft workforce aims to ensure that workers have control over their own data and enhance their use for their own benefit. Directly or after processing the data, the productivity performance information can be shared and negotiated by the users according to their desire and convenience. For examples of possible shares, amount others:

- Social networks;
- Curriculum;
- Employer;
- Recruiter;
- Insurers;
- Government agencies;
- Business entities.

Once again, the Worker 4.0 slogan "my work, my data" highlights the concept of workers' ownership of data. Figure 8.2 presents the Worker 4.0® business model canvas,

The solution is conceptualised and based on Fiware (IoT software platform) with the user interface through a mobile application. The embedded hardware app (smartphones and tablets) should collect, integrate, store and transmit information about its use and data from other devices. The solution is also allowing the user to configure the settings and business rules of the system. Figure 8.3 presents the system's components designed.

The data collected by the app devices are pertinent to the location, speed and acceleration, time in use of other applications, and input of actions by the user. Still, it should have the ability to collect, store and transmit data from other devices, wearables, equipment and machines.

Finally, the use case diagram drafted in Figure 8.4 provides a detailed visualisation of employees/employers information interaction and relationship, providing a view of that craft workforce piece of information (e.g. acceleration, geolocation, heart rate) to be shared. Figure 8.5 presents the system class diagram, where this ontology information flow provides a systemic view of the data and the systems/formats necessary to deliver useful information.

Key Partners
- C-level networking;
- Leaps;
- Fiware Consultant;
- Software Developers;
- FEUP;
- Start-ups accelerators;
- Investors;
- Fiware institution.

Key Activities
- Initial design;
- Initial structuring of the Project;
- Fiware development;
- App interface;
- Different devices integration;
- Partnership agreements.

Key Resources
- Time to develop and implement;
- Teams to manage and develop;
- Trademark patents and copyrights;
- Physical structure;
- Budget.

Value Propositions
- Individual data ownership;
- Data privacy and security;
- Choose what data is shared;
- Methodology for monitoring and improving labor productivity;
- Development of metrics and benchmarking;
- Prioritization of tasks;
- Identification of productivity impact factors;
- Templates for methodologies and specific professional areas;
- Free version application for a limited use;
- Paid full version application for unlimited use;
- Full version Free, by Sponsor;
- Web module for detailed analysis;
- Integration of teams and projects;
- Artificial Intelligence for autonomous mapping;
- Voice identification;
- Recording and storage voice and image;
- Big Data.

Customer Relationships
- Selection of data sharing;
- IoT with privacy and security;
- IOS and Android app;
- Integration with wearables;
- Web module;
- Templates and Patterns;
- Tools and techniques of productivity management;
- Metrics and Benchmarking;
- Unit sale;
- Customizations;
- Coworking;
- Artificial intelligence;
- Voice Commands;
- Voice and image recording;
- GDPR compliance.

Channels
- Satisfied users;
- Wearables industry;
- Partner institutions;
- Social media;
- Advertising.

Customer Segments
Construction Industry (CI).

Cost Structure
- Engineering hours in research and development;
- Administrative and financial structuring;
- Marketing investment;
- Cloud and/or physical server;
- Project management.

Revenue Streams
0.2% Global GDP.
Where:
[10% CI x 0.5 Craft workforce x 4% opportunity to bottom-up approach]

Figure 8.2 – Worker 4.0: Business model canva

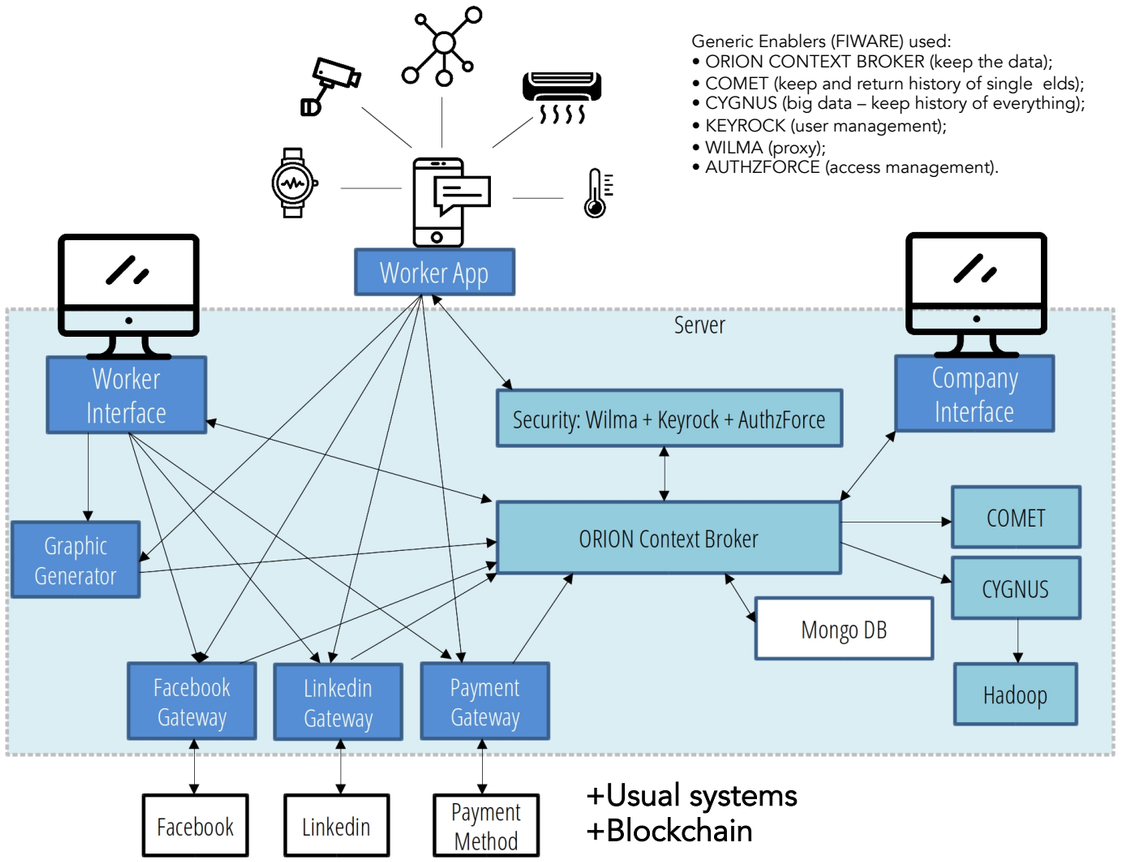


Figure 8.3 – Worker 4.0: System components.

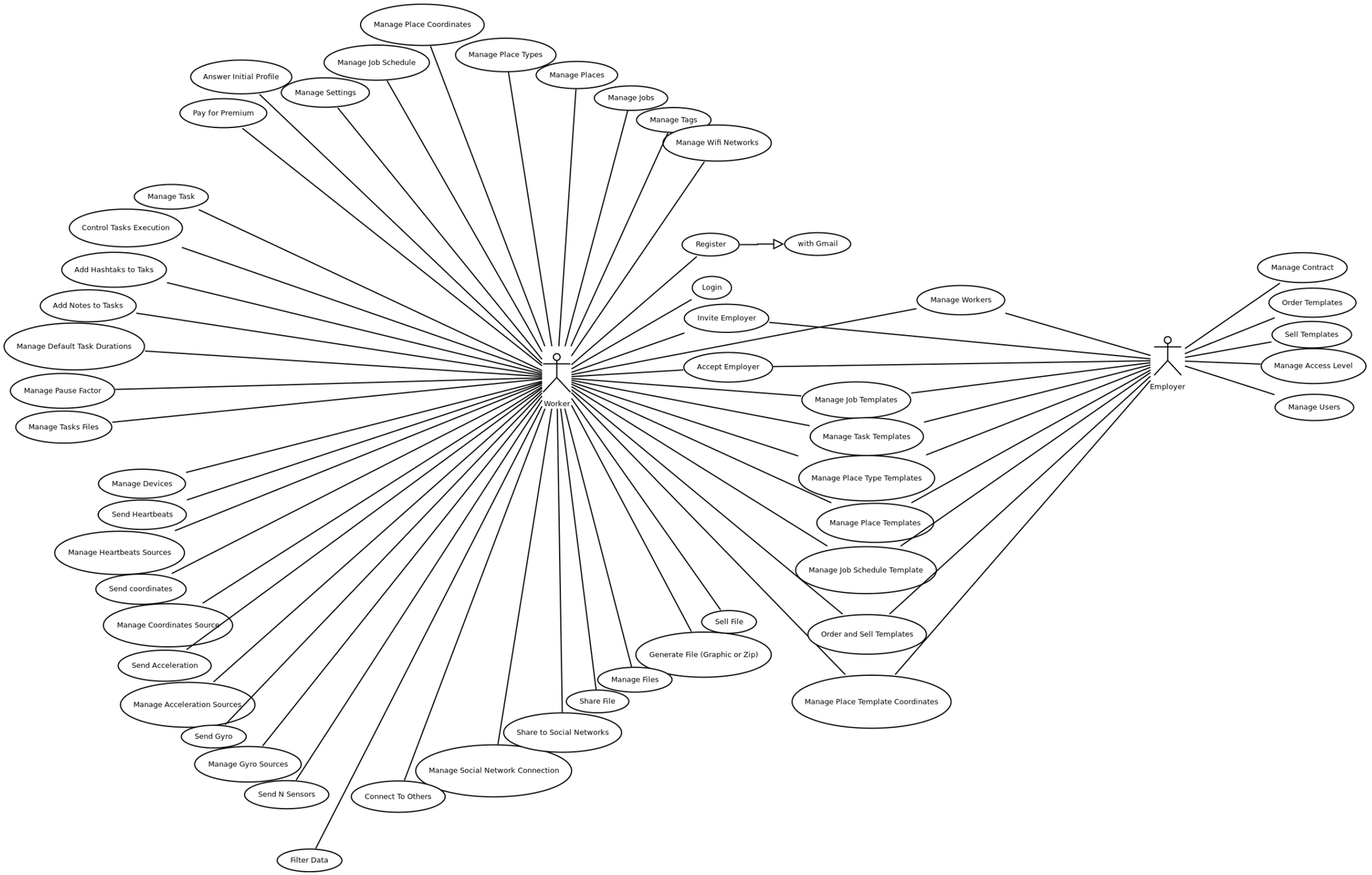


Figure 8.4 – Worker 4.0: Usage case diagram.

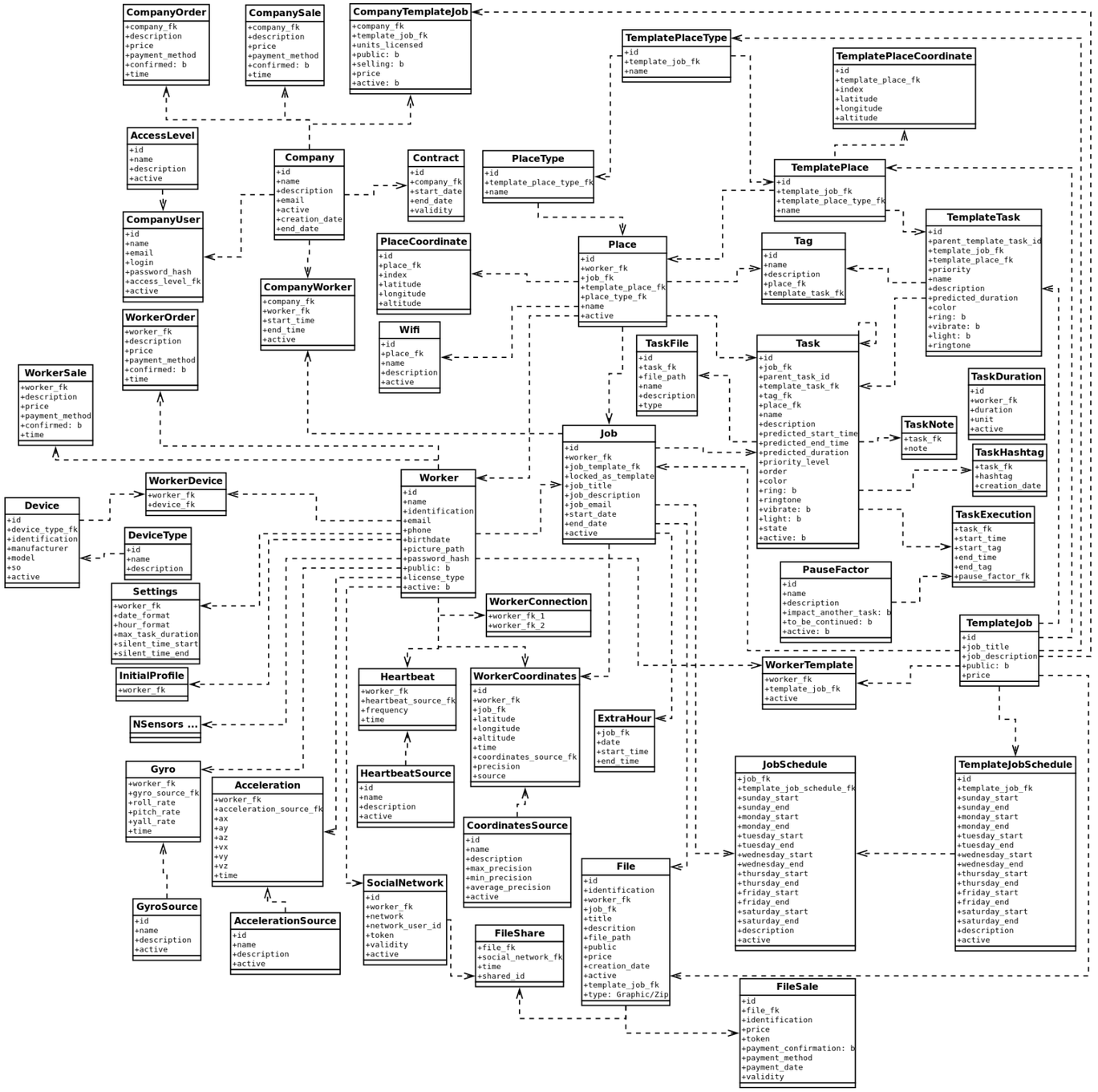


Figure 8.5 – Worker 4.0: Class diagram.

8.3.2 Future Research Approach

The added value of this work for the CI can be improved by integrating measurement methodologies and data collection devices. These, in addition to the improved support for the selection of the appropriate level of performance productivity assessment, these may allow, among others, the best integration with the human productivity factors and guidelines and awareness for the continuous improvement of workers' skills. Future research should interrelate the data of workers with products and equipment to integrate the scope of the construction sites. The information management pertinent mainly focusing on human data interaction across all construction project phases.

People, process, and technology are the vectors to achieve 4.0 status. Within the concept of Worker 4.0, stand out two main management fields of support as People Analytics and Workforce Planning, as presented in Figure 8.6. Methodologies like Organizational Network Analysis will enhance the development of high-performance teams. However, many different professional assets will be needed to develop innovation projects in this field. Furthermore, it is through multidisciplinary and inclusive work that Construction 4.0 will be enhanced.



Figure 8.6 – Knowledge integration.

In general, the findings suggest that if the processes are not developed taking into account the effect on people via regulations, e.g. GDPR and changing the culture, this can become a bottleneck to the implementation of the technology. This issue is in agreement with the hierarchy, which places human psychology and culture at the foundation of industrial practice. Further research can take into account this human dependency and apply more social scientific and psychological approaches.

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