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HUMAN-DATA INTERACTION AS A CRITICAL ENABLER OF ELECTRONIC PERFORMANCE MONITORING AT CONSTRUCTION SITES

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SUMMARY: *Human-Data Interaction (HDI) revolves around how humans generate, process, and utilise data. HDI plays a crucial role in evaluating data collection and use in the context of the construction industry, considering the impact on stakeholders such as site managers and labourers. One significant application of HDI is in on-site Electronic Performance Monitoring (EPM), which aims to leverage workplace innovations to enhance productivity, safety, and health. However, the integration and implications of HDI and EPM lack comprehensive understanding. This research seeks to bridge this knowledge gap by presenting a human-data perspective on sensored construction sites, emphasising the challenges and opportunities for driving innovative EPM initiatives. Through a combination of literature review, surveys with HDI experts, and the authors' perspectives and abduction, conceptual frameworks are developed that cluster HDI and EPM. The study's implications are multifaceted, impacting both theoretical understanding and practical applications. The findings highlight the key actors and the data they generate and manipulate across different platforms during EPM deployment. Through the lens of explanatory theories, sociomateriality, and work sociology, the research contributes to understanding the fragmented nature of HDI and EPM as a managerial issue embedded in the work environment. It sheds light on the interactions of actors using digital EPM devices and relevant data streams influenced by the limited agency of specific stakeholders, such as labourers, and the potential neglect of factors related to their well-being. This research distinguishes itself by focusing on the less explored intersection of HDI and EPM in the construction industry. It offers a novel perspective by considering the sensored environment of construction sites as a venue for analysing human-data interactions.*

KEYWORDS: *HDI, EPM, Electronic device, Construction management, Construction 4.0, Worker 4.0.*

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1. INTRODUCTION

The advent of innovations for Construction 4.0 is accelerating the use of sensing technologies at construction sites (McKinsey, 2017). Electronic device technology enhancements allow new ways of collecting and analysing human data (European Union, 2016; Ates et al., 2022). In that vein, the Electronic Performance Monitoring (EPM) (Lund, 1992; Schleifer and Shell, 1992; Alder, 2001) is a powerful element in evaluating on-site safety, health and productivity (Edirisinghe, 2019; Calvetti, Mêda, et al., 2020). Moreover, human-data interaction (HDI) also needs to be crucially considered to enable EPM deployment, which is characterised by legibility, agency, and negotiability for personal data collection and use (Mortier et al., 2014; Hornung et al., 2015; Victorelli et al., 2020). Therefore, raising awareness of HDI principles in the context of EPM's innovative initiatives in the construction industry is fundamental.

Smart-sensored construction sites can empower project management excellence (Edirisinghe, 2019). From supply chain tracking to 4D progress monitoring with an emphasis on the workforce, multiple electronic devices can populate construction sites (Edirisinghe, 2019; Calvetti, Mêda, et al., 2020). Furthermore, companies have long been using work monitoring tools, which can now be empowered by digital technologies (Alder, 2001). This empowerment includes the acquisition, process, and use of data; therefore, advanced data management systems should be compliant with the General Data Protection Regulation (GDPR) (European Union, 2016; Calvetti, Magalhães, et al., 2020). The GDPR European regulation, among other local initiatives, aims to rule data use and set fundamental rights and freedoms (European Union, 2016).

Beyond the human-computer interaction (HCI) concept based on evaluating human and computer symbiosis, HDI emphasises active interaction with data from beyond passive consumption (Hornung et al., 2015). HCI was fundamental to the study of how humans interact with hardware elements and more usable systems interfaces (Mortier et al., 2014). However, HDI sets a complex data collection, processing, and analysis scenario with multiple uses (Hornung et al., 2015) and is fundamentally related to human data. Data ownership can be established in two leading roles: "Data Producer" and "Data Consumer" (Chowdhury and Dhawan, 2016). Under sensored construction sites, data shall be collected from many stakeholders such as craft workers, operators, designers and managers – and its utilisation may then require the implementation of advanced digital technologies. For example, artificial intelligence (AI) might support workforce management decision-making, and blockchain technology can streamline contractual clauses (Calvetti, Magalhães, et al., 2020). However, it is a challenge to profile and analyse personal data, as algorithmic bias can exist in relevant applications from the outset (Sivarajah et al., 2013; Turner Lee, 2018; Dwivedi et al., 2021). Thus, reflections on HDI should also set the human-in-the-loop, bringing awareness to transparency, fairness and equity issues in data acquisition and use.

Researchers have been developing frameworks, systems, hardware tests and development, data classification and processing methodologies, and other proof-of-concepts concerning Information Technologies in the Construction Industry for many years. Meanwhile, advances are made in the technological field; multiple social and legal challenges claim attention, such as workforce data protection and personal rights. As a result, many technically validated applications cannot be upscaled in construction sites, sometimes due to a lack of GDPR compliance and many others due to adverse workforce reactions. In this, innovative implementations' lack of scalability and feasibility prevents increased on-site productivity, health, and safety performance, and it is a problem.

As multiple types of electronic devices can be applied for EPM in construction sites, methodological, computational and software systems are needed to manipulate and process a large amount of collected data. Ultimately, understanding the relevant construction stakeholders' regarding EPM initiatives targeting the principles of HDI is crucial. In the theoretical field, HDI plus EPM are meant to be an umbrella concept to cover the research in computing in construction connected to monitoring and increasing performance. With this awareness, researchers developing and testing EPM-based features may be able to lead future practical deployments better. Based on that, and supported by the literature review presented next, the research question raised is, "What theories and constructs could enhance the understanding of the HDI study field and improve EPM methods' scalability and feasibility, boosting real case deployments?".

Therefore, the research aim of this work is to integrate HDI and EPM in the context of construction sites by highlighting the challenges of using electronic devices to acquire and process human-related data. For this, a literature review on HDI and EPM in the context of construction sites was conducted, and the respective research gap in the integration of the two concepts is highlighted. This was then expanded with empirical work comprising a survey among related experts and a synthesis of the literature and survey results through the authors' analysis. Finally, this study contributes to raising awareness about the importance and intricacies of integration between HDI and EPM when applied in construction sites.

2. METHOD

A review was conducted to map the existing research in the area of HDI and EPM at sensored construction sites. At the same time, a comprehensive background was set to emphasise the research field of computing in construction and publications targeting construction performance issues – which, however, do not address HDI or EPM. The searches were based on title-abstract-keywords criteria and carried out in the scientific databases Scopus and Web of Science during late 2022, using a combination of keywords such as: “human data interaction"; "human data interaction" AND industry OR construction OR site OR onsite OR on-site OR "electronic performance monitoring" OR EPM OR performance; "electronic performance monitoring" OR "sensored sites" OR "digital skin" OR "electronic monitoring" OR "sensing technologies onsite" AND "construction". Based on that, 139 documents were first identified for review. After exclusion and inclusion criteria, 25 articles remained to be analysed, plus EPM-based papers were added to highlight the research gap (EPM disconnected from HDI principals).

Following the literature review, survey forms were emailed to thirty-two HDI experts, where twenty experts were identified by their publications in the HDI subject, plus twelve experts based on their participation in the HDI committee of The European Council on Computing in Construction (EC3) (https://ec-3.org/governance/technical-committees/human-data-interaction-committee/). The HDI committee reports to the EC3 board and promotes the research and innovation connected to the human-data interaction (Human-Data Interaction Committee, 2019). Subsequently, a nonprobability sample of experts in HDI with possible awareness of EPM was identified by mapping relevant publications and the practice on the subject and selected to provide feedback about HDI&EPM and the framework's conceptualisations. Although this purposive sampling (also known as judgmental sampling) may lead to some results bias, its selection was a methodological choice that emanated from the consideration that such a specific theme could be better discussed with experts than the general public (Bhardwaj, 2019). Significantly, researchers and practitioners are usually unaware of HDI and EPM perspectives. It achieved an 18.75% response rate, as six experts responded. The respondents' expertise and sample characteristics can be seen in Table 1. However, the experts are based in Europe; they may come from different regions with distinguished backgrounds. At the same time, due to the nature of the purposive sample, no more specific information is mentioned to avoid unveiling the experts' identities.

Table 1: Experts surveyed.

Expert	Region based	Professional experience	HDI experience
1	Northern Europe	10 to 20 years	8 years
2	Western Europe	2 to 5 years	5 years
3	Western Europe	2 to 5 years	5 years
4	Southern Europe	10 to 20 years	4 years
5	Southern Europe	< 20 years	5 years
6	Southern Europe	5 to 10 years	10 years

The delphi-survey was developed in two rounds. To create and evaluate the frameworks combining HDI & EPM, the authors used abductive reasoning. The first investigated the EPM and HDI concepts over specific groups of technologies. The second was conducted to collect impressions on new conceptualisations in HDI linked to data collection for EPM. Figure 1 illustrates the communication framework between the experts and the authors.

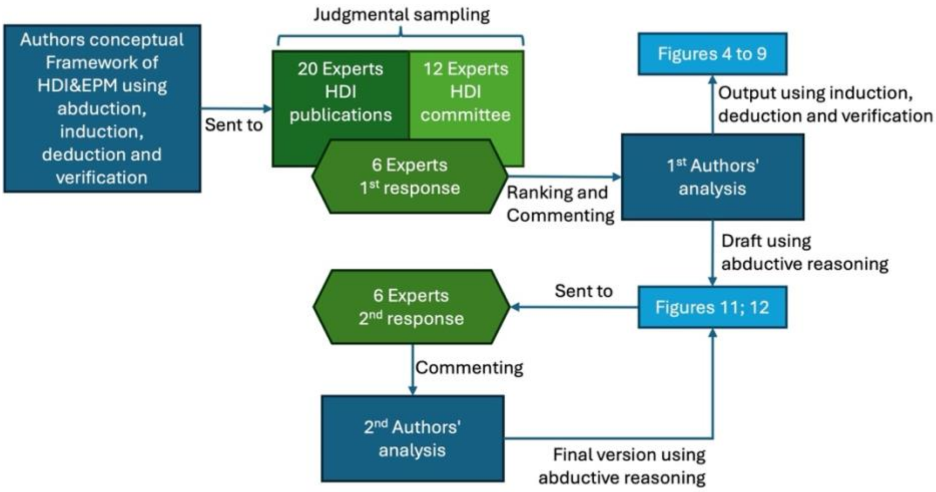


Figure 1: Communication framework between the experts and the authors.

The first survey set questions on HDI and EPM over clustered tools (Portables, Wearables, Images, Automated embedded systems, Sensors, Computational and Software) at the Construction Sites. For example, IoT, Eye tracker glasses, IMU - inertial measurement units, Electroencephalography, Drones and VR – Virtual Reality. There are three main types of work systems in construction. The first is manual work, where workers use their hands and may use some manual tools to perform tasks like laying bricks and painting (Groover, 2007). The second is worker-machine systems, where workers use machines or equipment to complete tasks, like drilling holes or using a backhoe (Groover, 2007). The third type is automated systems, where machines perform tasks without direct input from workers, and workers only monitor the process (Groover, 2007). These systems are often combined to build construction elements using raw materials, products or elements/systems. Based on that, this study highlights elements and stakeholders such as:

Workforce

- Blue-collar workers include Craftworkers (e.g., carpenters, ironworkers, masonries) and Operators of equipment (e.g., cranes, excavators) or vehicles (e.g., backhoes, forklifts). In this, that workforce refers to those directly using physical effort to conduct the on-site tasks.
- White-collar workers encompass administrative roles, project and contract management, and architecture, emphasising intellectual and strategic abilities over physical labour. Mainly at the construction sites, it will be related to Geophysicists/Geologists, Designers, Managers and Office workers.
- IT workers, however, may be classified as White-collar workers; in this work, they are segregated as a specific class of workforce that will deal with innovative projects, mainly deploying EPM. Usually, they work off-site, partially being on-site when implementing innovative projects or conducting PoCs (proofs-of-concept). For example, workers can be Software architects, Computer programmers, and Data scientists, among others.

Assets

- Raw materials (e.g., sand, gravel);
- Construction products for applications (e.g., brick, metal beams);
- Construction-engineered elements/systems (e.g., windows, prefabricated wall panels).

Instruments

- Hand tools (e.g., drill, saw);
- Machines (e.g., ink sprinkler, welder machine);
- Equipment (e.g., backhoe, crane).

The first survey set use cases of EPM deployment over construction subjects, asking experts to select the most relevant issues correlated with them and to provide open answers regarding barriers and opportunities in the HDI spectrum of that use case scenario. The authors discussed the quantitative results of the experts' survey and summarised an in-depth understanding of HDI and EPM at construction sites. The insights from HDI and EPM were captured in frameworks that present distinguished vectors of human-data interaction between multiple target elements to be monitored. Figure 2 summarises the research approach, starting with a literature review and then a Delphi survey to allow a knowledge base for the next frameworks made regarding HDI and EPM.

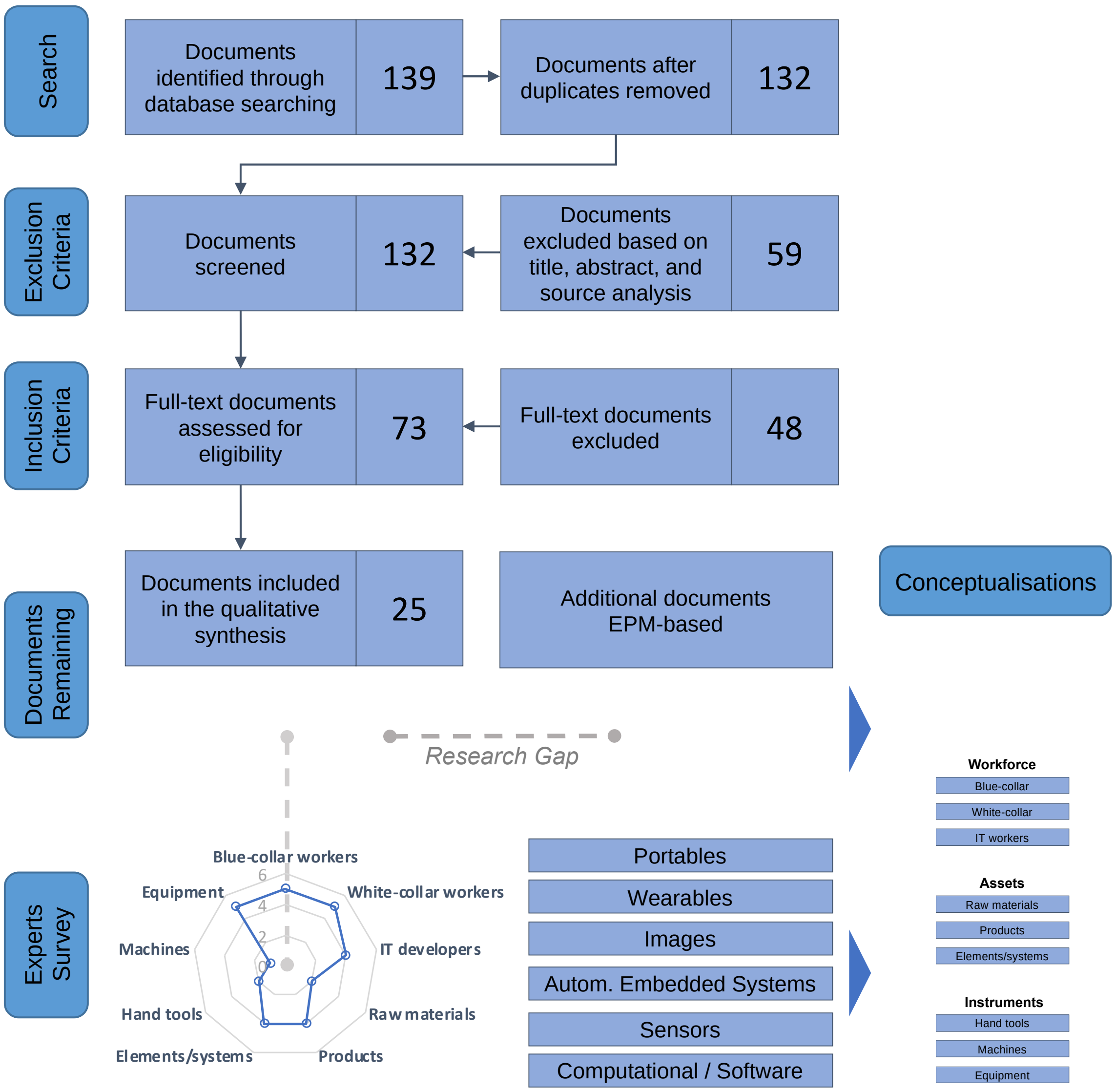


Figure 2: Research workflow diagram.

3. REVIEW CONTENT ANALYSES

Most studies collected in the search combining HDI & EPM focus on the UX (user experience) and UI (user interface). It can be seen that most of the research is theoretical or artefact/systems-research-based. Also, research contributions in the fields of empirical/experimental, workshop proposal, challenges mapping/review, and position/opinion were noted. Finally, some publications do not target any specific group of people, just delivering overall concepts. Table 2 summarises the papers from the HDI plus EPM perspective due to their research contributions.

Table 2: HDI-EPM research contributions, content analyses.

HDI-EPM research contributions	Number of studies	Authors
UX (user experience)	7	(Sivarajah et al., 2013; Hutton and Henderson, 2017; Jones, Sailaja and Kerlin, 2017; Widjojo, Chinthammit and Engelke, 2017; Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019; Victorelli et al., 2019)
UI (user interface)	3	(Vasuki et al., 2014; Gan et al., 2018; Victorelli and Reis, 2020)
Artefact/systems-research-based	7	(Mashhadi, Kawsar and Acer, 2014; Jones, Sailaja and Kerlin, 2017; Gan et al., 2018; Santos, Salgado and Viterbo, 2018; Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019; Victorelli et al., 2019)
Empirical/ Experimental	4	(Sivarajah et al., 2013; Vasuki et al., 2014; Brombacher, Houben and Vos, 2022; Calvetti et al., 2022)
Workshop proposal	2	(Wolff et al., 2018; Sailaja et al., 2021)
Challenges mapping/ Review	1	(Victorelli et al., 2020)
Position/ Opinion	1	(Doan, 2018)
Overall concepts	15	(Mashhadi, Kawsar and Acer, 2014; Hornung et al., 2015; Chowdhury and Dhawan, 2016; Crabtree, 2016; Hutton and Henderson, 2017; Jones, Sailaja and Kerlin, 2017; Widjojo, Chinthammit and Engelke, 2017; Doan, 2018; Santos, Salgado and Viterbo, 2018; Wolff et al., 2018; Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019; Victorelli and Reis, 2020; Victorelli et al., 2020; Sailaja et al., 2021)

A few studies personated subjects that are often suitable for monitoring, such as people, materials, or machines. There were studies targetting specific construction workers (White/Blue-collar), Geophysicists or Geologists, Designers, Facility managers, and general Office workers. Finally, just one study focused on construction machines; see the overall subject perspective in Table 3.

Table 3: HDI-EPM subjects' perspective, content analyses.

Subjects' perspective	Number of studies	Authors
White/Blue-collar workers	4	(Edirisinghe, 2019; Calvetti, Magalhães, et al., 2020; Calvetti, Mêda, et al., 2020; Calvetti et al., 2022)
Geophysicists or Geologists	2	(Sivarajah et al., 2013; Vasuki et al., 2014)
Designers	1	(Victorelli et al., 2019)
Facility managers	1	(Gan et al., 2018),
Office workers	1	(Brombacher, Houben and Vos, 2022)
Construction machines	1	(Tian et al., 2013).

In addition, most studies have not mentioned the use of electronic devices. However, discussions on IoT (Internet of Things) or conceptualisations on multiple sensors were observed. It was also possible to identify some specific electronic device applications such as Eye tracker glasses, IMU - inertial measurement unit, Electroencephalography, Drones and VR – Virtual Reality. Table 4 summarises the electronic devices identified in the publications. Finally, just a few studies focused specifically on human performance monitoring.

Table 4: HDI-EPM electronic devices use, content analyses.

Electronic devices use	Number of studies	Authors
IoT (Internet of Things) or conceptualisations on multiple sensors	8	(Tian et al., 2013; Mashhadi, Kawsar and Acer, 2014; Chowdhury and Dhawan, 2016; Crabtree, 2016; Gan et al., 2018; Edirisinghe, 2019; Calvetti, Magalhães, et al., 2020; Calvetti, Mêda, et al., 2020)
Eye tracker glasses	3	(Sivarajah et al., 2013; Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019)
IMU - inertial measurement unit	2	(Brombacher, Houben and Vos, 2022; Calvetti et al., 2022)
Electroencephalography	1	(Sivarajah et al., 2013)
Drones	1	(Vasuki et al., 2014)
VR – Virtual Reality	1	(Widjojo, Chinthammit and Engelke, 2017)

In short, the analysed publications demonstrated a disconnection between the subjects of HDI, EPM and electronic devices for construction site applications. Most of EPM's terminology and concepts came from the field of social and technology management research. Although construction management research using electronic devices is developed in the academic and business areas, less attention has been afforded to the formal spectrum of EPM. Adding to this, the HDI domain is relatively new and has not yet been perceived over technical use cases or actual applications in the construction industry. In the following subsections, the HDI and EPM subjects will be discussed in detail based on the conducted review and a few more articles related to EPM that did not indicate such a concept but applied it.

3.1 Human-data Interaction (HDI)

Most research efforts tend to investigate HDI from the perspective of how humans visualise and use data (Sivarajah et al., 2013; Vasuki et al., 2014; Hutton and Henderson, 2017; Jones, Sailaja and Kerlin, 2017; Widjojo, Chinthammit and Engelke, 2017; Gan et al., 2018; Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019; Victorelli et al., 2019; Victorelli and Reis, 2020). Also, some studies analyse aspects of data processing, such as AI decision-making tools (Calvetti, Magalhães, et al., 2020). As realised by Victorelli et. al. (2020), most research regarding personal data is connected to domains such as music, food-eating habits, and health-related (Victorelli et al., 2020). HDI is also correlated to UI, data analyses, human cognition, psychology, and behavioural science (Widjojo, Chinthammit and Engelke, 2017).

The HDI landscape of UI and UX is closely connected to the semiotic perspective of sign visualisation, where data is more correlated with syntax and information in the semantics (Hornung et al., 2015; Victorelli et al., 2019). The design of systems using HDI principles allows both to maximise UI/UX for data visualisation and facilitate the selection of data exchange options (Jones, Sailaja and Kerlin, 2017; Victorelli et al., 2019). Also, ontology visualisations can be better adapted to human interaction (Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019). Finally, electronic devices based on Virtual Reality (VR) can empower human capabilities to visualise and analyse data (Widjojo, Chinthammit and Engelke, 2017). VR can support HDI by providing immersive visualisation, presence sense, spatial awareness, natural interaction, and command responsive feedback (Widjojo, Chinthammit and Engelke, 2017). HDI research is also related to data ownership, privacy and consent (Mashhadi, Kawsar and Acer, 2014; Chowdhury and Dhawan, 2016; Crabtree, 2016; Hutton and Henderson, 2017). Concerning data ownership at the city scale, Chowdhury and Dhawan (2016) envisaged five possible electronic device data use models (Chowdhury and Dhawan, 2016): Unrestricted data models (the information might be accessed and used for systems application by people, governments or industries without restrictions);

- Semi-restricted data models (data owners can opt-in to share general or personal information);
- License-restricted data models (data pre-defined shareable models);
- Pay-per-usage models (data owners shall receive payments every time their data is acquired);
- Fully restricted data models (regarding strategic data, such as for military purposes).

These kinds of data ownership models can also be pertinent for construction industry applications as possible uses of electronic devices provided by employers or employees with consent. Moreover, previous agreements should regulate general or personal data use, qualifying types of generalistic, sensitive and licensed data from providers and consumers (Chowdhury and Dhawan, 2016; Calvetti et al., 2021). Adding to that, GDPR legislates the rights of data providers and the obligations of data consumers in Europe (European Union, 2016; Calvetti, Magalhães, et al., 2020). European Union member states are allowed to regulate personal data pipelines that best fit local laws specifically (European Union, 2016). Personal data processing must be transparent, lawful and fair (European Union, 2016). Systems that manipulate personal data must be secure and confidential, preventing unauthorised access (European Union, 2016). Finally, Victorelli et al. (2020) raise a broad HDI research challenge with the following topics:

- Personal data legibility and agency;
- Users' engagement through participation in design processes;
- Models and value of data ownership;
- Social and cultural aspects;
- Semantic understanding of data;
- Transcending human and machine limitations in data analysis;
- Challenges to embodied interaction;
- A systemic view of the complete data life cycle;
- Data influence in decision-making process;
- Support for interaction in specific activities or domains (Victorelli et al., 2020).

Ultimately, HDI's vast body of knowledge can support innovation in EPM. Through that lens, putting humans at the centre of innovation and mapping data collection-use interaction is crucial. Stakeholders that are well-informed about this can thus be more engaged. HDI foundations account for all legitimate interests of the data users, system developers and data providers. HDI focuses on the interactions between individuals and data, ensuring that these interactions are trustworthy, meaningful, and comprehendible. HDI goes beyond the traditional HCI by considering people's interaction with data, aiming to make data more accessible and relevant to human users. From a knowledge-sharing perspective, HDI can potentially improve communication between humans and data, making complex data understandable to a broader audience. HDI supports the dissemination of knowledge by providing transparent and trustworthy data representations. In summary, HDI serves as a bridge between data and people, enhancing knowledge sharing and facilitating more accurate explanations of phenomena.

3.2 Electronic Performance Monitoring (EPM)

The advances of computational technologies in workplaces over the 1980s raised speculations about management and organisational psychology, which have been oriented to studies by the Office of Technology Assessment (OTA) in the USA Congress (Eisenman, 1986). During the 1990s, the terminology "Electronic Performance Monitoring" gained shape in the field of management research (Lund, 1992; Schleifer and Shell, 1992; Fenner, Lerch and Kulik, 1993; Kolb and Aiello, 1996; Alder and Tompkins, 1997). Nowadays, the theme is relevant due to electronic advances and the massive use of relevant devices. Nonetheless, the concept of performance standards is vast but mainly correlated to productivity and safety (Schleifer and Shell, 1992). Undoubtedly, electronic performance monitoring might lead to workforce reactions related to stress, discontent and disagreement (Schleifer and Shell, 1992; Smith et al., 1992; Alder, 2001).

Considering specific EPM technologies, wearable gadgets that can be hung on one's neck, attached to a belt, or placed over a desk while one is working can use multiple data sources to monitor office environments (Brombacher, Houben and Vos, 2022). Electronic wearables such as eye-tracker glasses (Sivarajah et al., 2013; Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019) and electroencephalography (EEG) skull caps (Sivarajah et al., 2013) can monitor users' behaviours when analysing data. In a study, geophysicists and geologists wearing eye-trackers and EEG devices classified magnetic data from images, and their success rate was evaluated; the results indicated that the orientation of the photos was more relevant than the sequence presentation (Sivarajah et al., 2013). Also, the users' ontology visualisation behaviour was monitored using eye-tracker glasses and mouse click data. Results demonstrated that data visualisation could be improved in real-time based on the user’s data personification (Fu and Steichen, 2019; Fu, Steichen and Zhang, 2019).

Multiple sensors and IoT technologies can monitor industrial machinery and construction equipment (e.g., mining trucks) (Tian et al., 2013; Gan et al., 2018). Sensing technologies can enable data collection from construction sites (Edirisinghe, 2019; Calvetti, Mêda, et al., 2020). For example, drones can capture land images, including detailed information about rock surfaces (Vasuki et al., 2014). Data can be collected from products and machines, and the information evaluation can infer the performance of workers and operators. Using IMU acceleration data, it is possible to classify blue-collar workers' performance in detail, even in basic tasks such as hammering, sawing and painting (Calvetti et al., 2022). However, personifying human performance is a challenge (Mashhadi, Kawsar and Acer, 2014; Jones, Sailaja and Kerlin, 2017; Calvetti, Magalhães, et al., 2020). EPM must bring transparency, and data outcomes should be shared (Chowdhury and Dhawan, 2016; Doan, 2018; Calvetti, Magalhães, et al., 2020; Brombacher, Houben and Vos, 2022).

Overall, construction productivity is connected to the project's design, procurement, construction, use and deconstruction. EPM at offices can assess white-collar workers' productivity by evaluating environmental aspects and outcomes (Brombacher, Houben and Vos, 2022), while the on-site construction tasks are more related to blue-collar workers and the techniques of using tools and machines to manipulate construction products to build the desired projects (Edirisinghe, 2019; Calvetti, Mêda, et al., 2020). Multiple stakeholders, such as IT developers, are demanded to deploy innovative EPM-based projects. As a result, multiple-use-type electronics are prone to be applied at sensored construction sites (Edirisinghe, 2019; Calvetti, Mêda, et al., 2020; Brombacher, Houben and Vos, 2022).

Real-time location systems (RTLS) would require multiple portable and wearable devices to monitor workers, tools, materials and machines. Methods to acquire position and processing data of tagged items for occupancy and pathways have been improved over time (Ibrahim and Moselhi, 2016; Valero and Adán, 2016). Positioned gates can monitor the in-out of workers, materials and machines (Kelm et al., 2013; Guo, Luo and Yong, 2015), including the evaluation of whether the workers are wearing PPE (Personal Protective Equipment) (Kelm et al., 2013). Equipment operations can be monitored (Oloufa, Ikeda and Oda, 2003; Pradhananga and Teizer, 2013) as dynamic paths can be reproduced (Cheng et al., 2011; Pradhananga and Teizer, 2013). Monitoring assets' location across the densest construction sites is crucial to enhance performance (Montaser and Moselhi, 2014; Li et al., 2017). The electronic monitoring of the tools used to perform the tasks allows activity classification and inferences of productivity and quality performance (X. Yang et al., 2019). Collecting personal data from wearables integrated into environmental sensors allocated in buildings and sites can lead to comfort and performance monitoring (Jayathissa et al., 2020). However, continuous location monitoring may lead to overcontrol; therefore, EPM management research can provide insights into what people think, and HDI may support considerations of workers' satisfaction and acceptability.

Furthermore, workers’ motions can be monitored to classify on-site actions to evaluate productivity (Akhavian and Behzadan, 2016; Zhang et al., 2018), health (Yan et al., 2017) and safety (Z. Yang et al., 2019; Duan, Zhou and Tao, 2022), as workforce physiological reactions are connected to the site's physical condition and can impact performance. For this, multiple sensors can monitor indoor (Jang, Healy and Skibniewski, 2008) and outdoor (Riaz et al., 2014) environments, as well as confined spaces (Ren et al., 2022). For the workers themselves, special wearable devices using EEG, ECG, and PPG technologies allow monitoring, among others, brain waves, heart rate, blood pressure, and oxygen saturation (Chen, Song and Lin, 2016; Hwang et al., 2016; Hwang and Lee, 2017; Lee et al., 2017; Jebelli, Hwang and Lee, 2018; Ryu et al., 2019). In addition, the workers’ skeletons’ 3D processing allows in-depth posture recognition for monitoring health and productivity (Khosrowpour, Niebles and Golparvar-Fard, 2014; Yu et al., 2017), and 3D full-body pose tracking and VR wearables allow simulations and training (Kurien et al., 2018). However, wearable devices for EPM are very intrusive, especially regarding the workforce's physiological assessment. As a principle, all kinds of innovative deployment in this field must be GDPR compliant, and HDI principles may support the best decisions when conceptualising on-site applications.

Mixed vision glasses (wearables) can support the on-site workforce (Kim, Kim and Kim, 2017). The use of images has an extensive range of applications and has been improved over time (Chen and Wang, 2017; Han and Golparvar-Fard, 2017). On-site outdoor 2D images can be used to monitor workers (Yang et al., 2010; Son et al., 2019), equipment (Soltani, Zhu and Hammad, 2017) and both (Memarzadeh, Golparvar-Fard and Niebles, 2013;

Kim, Kim and Kim, 2016). Moreover, indoor 2D recordings can be checked to monitor the progress of tasks (Hamledari, McCabe and Davari, 2017), and outdoor RGB images can be used for 4D CAD model updates (Kim, Kim and Kim, 2013). At the same time, UAVs (Unmanned Aerial Vehicles), also named drones, can potentially increase the quantity and quality of image collection (Dupont et al., 2017) for on-site uses such as safety inspection (Melo et al., 2017). Furthermore, laser scanning can render the built environment, allowing 4D model updates (Han and Golparvar-Fard, 2015). Nevertheless, the use of images may lead to personal identification, as privacy and data ownership are the main challenges for fair EPM applications. Again, HDI principles may orient an autoregulation of the relevant systems to face these barriers.

When it comes to (multi-)sensors, those can be embedded in machine systems targeting to monitor the physical and processual conditions of workpieces (Teti et al., 2010). Sensored equipment and tools imply fully monitored on-site activities, allowing increased productivity (Goodrum, McLaren and Durfee, 2006; Liu et al., 2016). With the potential use of multiple devices to collect on-site information, a significant amount of data is obtained and must be quickly and precisely processed to deliver the envisaged outcomes (Wang et al., 2020). AI using machine and deep learning can support such data processing (Baduge et al., 2022). Blockchain and digital twin trends should also boost data use and shareability (Lee et al., 2021; Li and Kassem, 2021). Finally, as big data from construction sites are mainly connected to workforce performance monitoring, algorithmic bias in the data processing systems must be avoided. To that end, HDI conceptualisations may support fairness and transparency. HDI's UI-UX practices may streamline workforce understanding and acceptance of data collection and processing innovations. In summary, the devices and tools for deploying EPM above identified were clustered in six groups, respecting their similar characteristics as i. Portables, ii. Wearables, iii. Images, iv. Automated embedded systems, v. Sensors and, vi. Computational and Software. Next, each cluster is detailed:

Portables

- RFID (Radio-Frequency IDentification), radiofrequency communication occurs basically through transponders or tags that can store information internally and use radiofrequency fields to exchange information with readers equipped with an antenna. The communication (reading) can be passive (active by the reader) or active (battery-based);
- UWB (Ultra-wide-band) is also a radiofrequency communication, mainly active, endowed with high bandwidth that can achieve an accuracy of 10 cm;
- GPS (Global Positioning System) is a network of orbiting satellites that transmit high-frequency radio signals with time and distance data to land-based devices from which to obtain their geographical location t
- IMU (Inertial Measurement Unit) are electronic devices equipped with a power supply combining multiple sensor types, such as accelerometers, gyroscopes, magnetometers, GPS, and UWB, among others (Fang and Dzeng, 2014);
- Smartphones, commercial devices.

Wearables

- Smartwatches, commercial wearables;
- Wristband, commercial wearables;
- Devices using Electroencephalogram (EEG) to measure brain activity using electrodes, Electrocardiogram (ECG) to measure the heart rate applied in wearables in the thoracic cavity, and Photoplethysmography (PPG) to measure the oxygen saturation levels in wearables using optical sensors;
- Mixed vision glasses (Google Glass, Microsoft HoloLens, etc.), commercial wearables.

Images

- 2D images (CCTV systems, photographic and film cameras, etc.) commercial devices.;
- 2D images (Drones - UAV, Unmanned Aerial Vehicle) commercial devices.;

- 3D images (Point cloud, motion capture systems, 3D camcorders, LiDAR) commercial devices.

Automated embedded systems

- Automated/sensored tools, machines and equipment (e.g., rigging equipment, welding machines).

Sensors

- Sensors for measuring environmental factors (e.g., temperature, noise).

Computational and Software

- Data visualisation, processing, and use (e.g., machine learning, deep learning, blockchain).

3.3 HDI and EPM taxonomy conceptualisation

Based on the review and using abductive reasoning stated in the Abductive Grounded Theory (Rahmani and Leifels, 2018), the authors developed a conceptual taxonomy correlating HDI and EPM. As illustrated in Figure 3, implementing EPM translates to data being collected from the workforce, tools and assets, providing information for management that will be consumed by multiple stakeholders where HDI practices enable compliance. Electronic devices are the vehicle of data collection and use. Therefore, the sensing technologies must be selected on the basis of both EPM target outcomes and HDI restrictions. Also, Victorelli et al. (2020) highlight the main HDI research challenges that can be arranged through the lens of data collection or use. Adding to this, instrumentalism posits that technology merely serves as a tool for accomplishing specific objectives (Fernandez, 2021). On the other hand, technological determinism may suggest a degree of independence, which could be attributed to the evolution of self-learning algorithms (Fernandez, 2021). Finally, as highlighted above, it is possible to classify the users as data producers or data consumers (Chowdhury and Dhawan, 2016).

This implies that when a researcher or a company employs ICT to gather data at a construction site, it involves extracting data from a product, machine, or worker. In this scenario, the sensing technologies are the tool for this purpose, aligning with the instrumentalism theory. Conversely, workers operating machines and/or manipulating products under electronic surveillance will generate data, and processing this data through algorithms could potentially invoke the principles of the technological determinism theory.

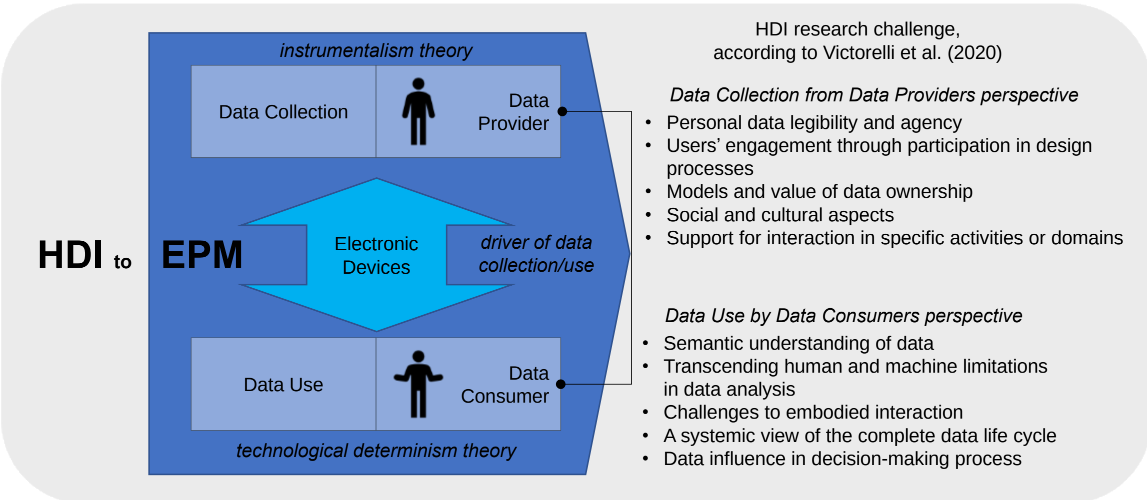


Figure 3: HDI to EPM taxonomy.

4. HDI TO EPM AT CONSTRUCTION SITES

4.1 Experts' interpretations

Analysing the experts' responses concerning HDI and EPM made it possible to identify common concerns such as privacy, data safety, and awareness. The generic use case is related to blue-collar workers being electronically monitored when conducting usual duties on-site manipulating assets and instruments. Although white-collar workers can also be monitored, their role is most prone to use the information to manage on-site. IT developers will also support data collection and analysis. Figures 3-8 represent the experts' indication of the most suitable EPM subject targets for each use type of electronics and the highlighting of HDI barriers and opportunities. The authors' meetings were held to consolidate the survey data and design the figures for the summarisation of the survey outcomes.

The portable devices used for EPM are more suitable/preferable/appropriate with blue/white-collar workers, equipment (e.g., backhoe, crane), construction products (e.g., brick, metal beams), and elements/systems (e.g., windows, prefabricated wall panels), as represented in Figure 4. Finally, the HDI barriers are closely related to people's awareness, and the HDI opportunities are more related to data use.

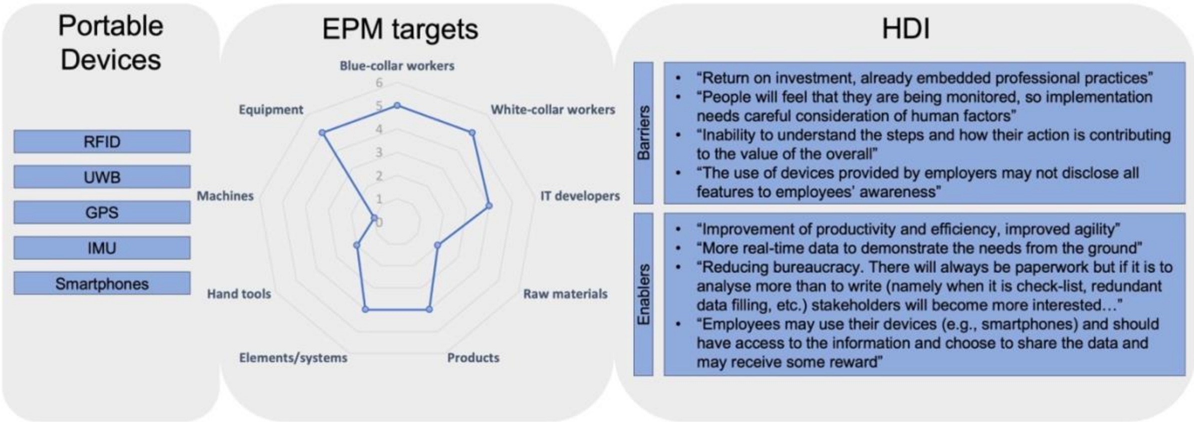


Figure 4: Portable devices, Experts analysis.

The use of wearable devices for EPM is closely connected to the blue and white-collar workforce, see Figure 5. Consequently, HDI's main challenges are related to electronic gadgets worn by the workers. It should be noted that Google has discontinued the production of Google Glass, with the overall product support slated to end in September 2023.

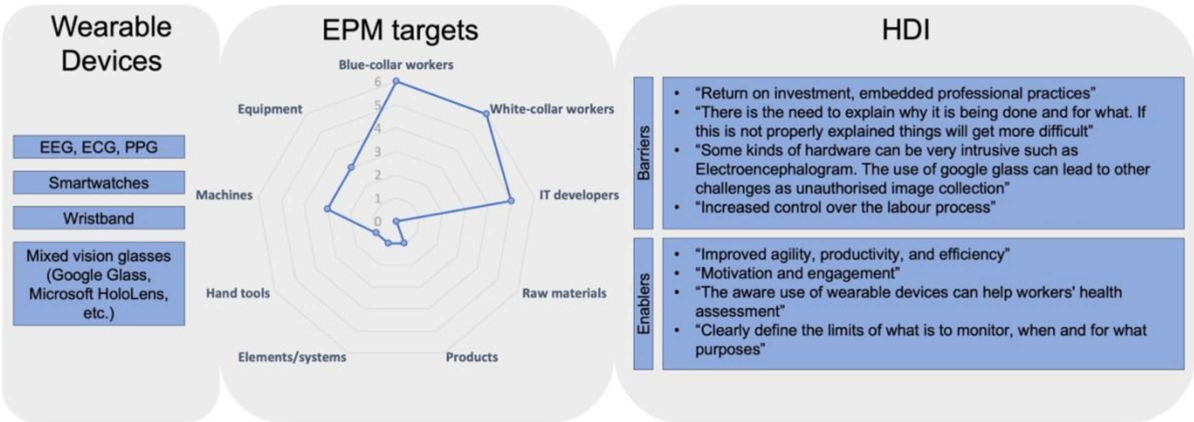


Figure 5: Wearable devices, Experts analysis.

Regarding the use of images, an expert highlighted that: "2D and 3D images can lead to an enormous amount of data being collected and transferred. Processing images can demand high computational capacity.". As presented in Figure 6, EPM using images can potentially monitor multiple subjects, with HDI privacy being the primary concern.

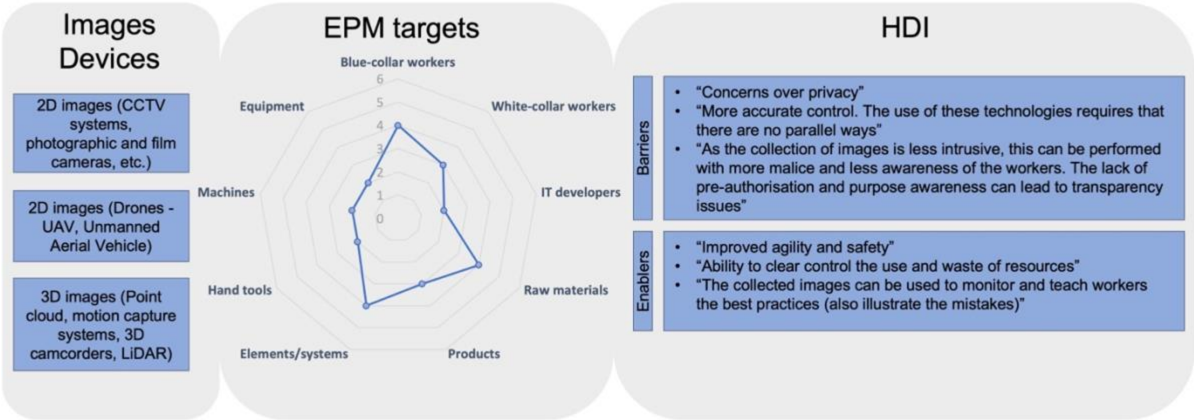


Figure 6: Image devices, Experts analysis.

Automated systems are already embedded in humans' routines; as an expert pointed out, our smartphones constantly collect data, and users are mostly unaware of this. Consequently, both barriers and enablers in HDI are connected to ethical limits and awareness. Figure 7 shows that experts visualised more EPM applications on-site targeting hand tools (e.g., drill, saw), machines (e.g., ink sprinkler, welder machine), construction elements/systems and blue-collar workers.

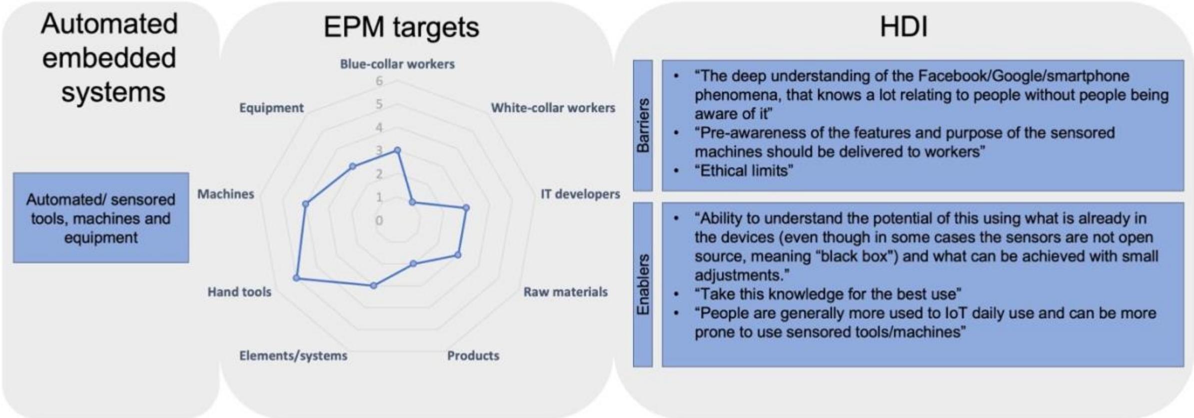


Figure 7: Automated embedded systems, Experts analysis.

Again, sensors and IoT are all over humans' daily lives. As experts highlighted, even the construction sites already use this sensing technology; see the example in Figure 8. With this, EPM is correlated to all subjects and potentially has fewer HDI barriers. However, the GDPR and HDI principles of transparency, equality and fair purpose must be followed.

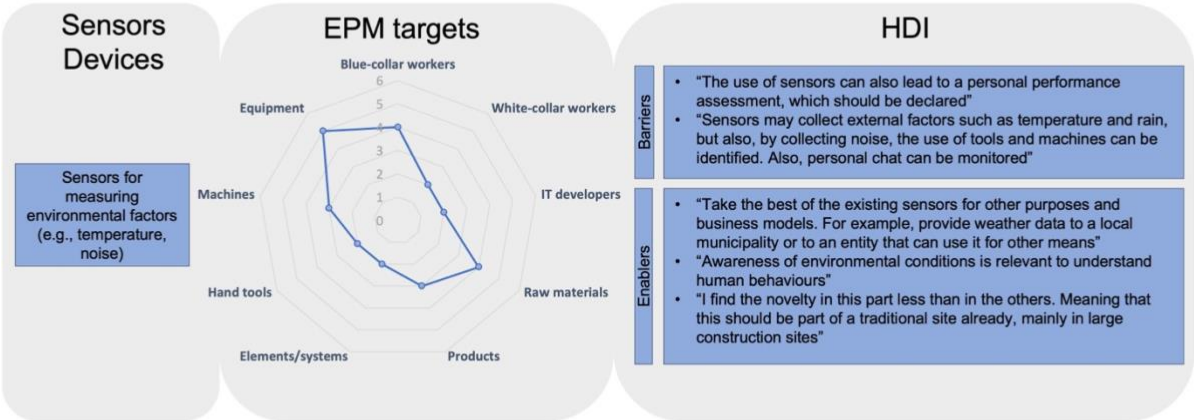


Figure 8: Sensors devices, Experts analysis.

Significantly, computational software solutions are correlated to data processing and visualisation. As a result, it can be seen in Figure 9 that the experts associated EPM targets with white-collar workers and IT developers. Finally, the HDI barriers raised were more linked to algorithmic bias, ethics and mistrust. Meanwhile, HDI enablers are connected to best practices and GDPR compliance.

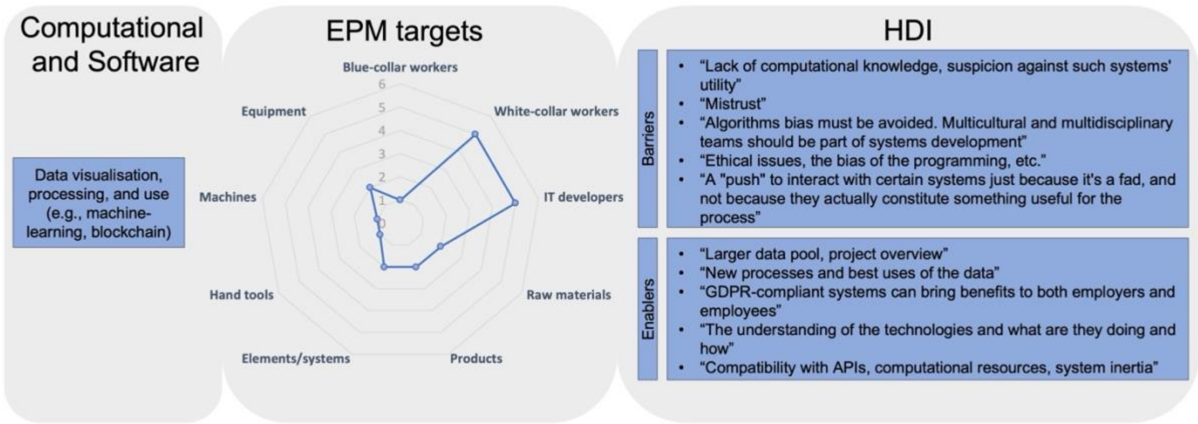


Figure 9: Computational and software, Experts analysis.

4.2 Findings and Conceptualisations

Based on the experts' interpretations and the literature reviewed, the authors could correlate EPM and HDI and raise some concepts regarding data use and technology theories, as presented in Figure 10. The EPM subjects can thus be classified as follows:

- Data Providers (Equipment, Machines, Hand tools, Elements/systems, Products, and Raw materials) are mainly providers;
- Data Providers and Consumers (Blue-collar workers) are mostly providers;
- Data Consumers and Providers (White-collar workers) can be both consumers and providers; however, they are more often consumers;
- Data Consumers and Providers (IT developers) are mostly consumers.

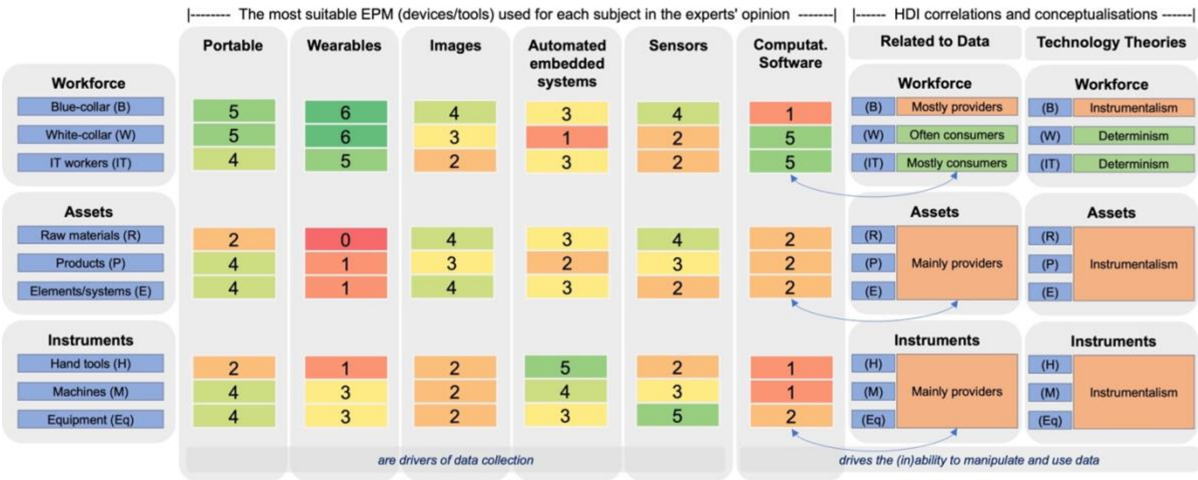
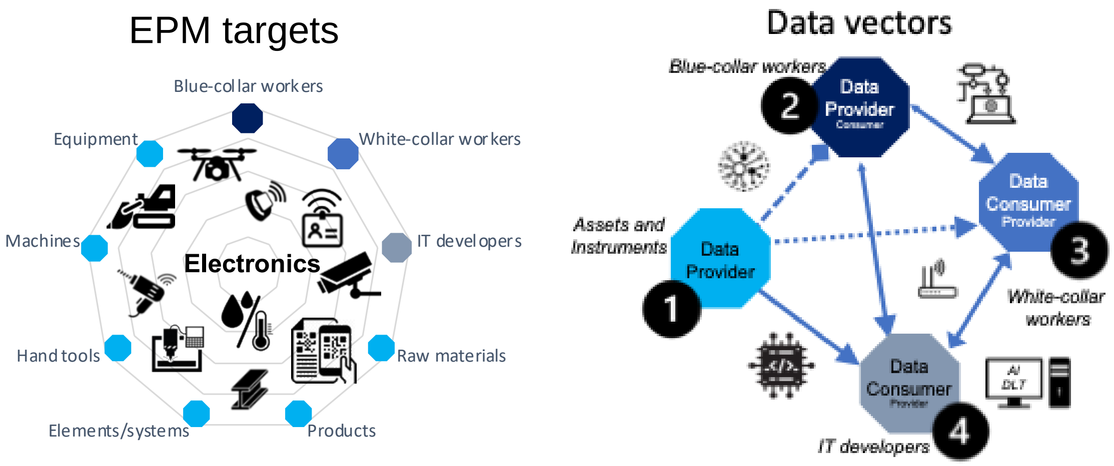


Figure 10: Clustering and classifying EPM and HDI interaction.

Based on the review and the survey analyses, it is possible to envisage how the HDI domain is a critical element in EPM deployment at construction sites. To develop Figures 11 and 12, the authors used abductive reasoning to conceptualise the knowledge from the literature review and the experts' comments. Accordingly, EPM targets multiple subjects, as represented in Figure 11(a); consequently, subjects can be clustered as Data Providers/Consumers, and HDI data vectors can be found in Figure 11(b), where HDI vectoring can be identified as:

- Data vectoring 1 “Data Provider” to 3 “Data Consumer and Provider”;
- Data vectoring 1 “Data Provider” to 2 “Data Provider and Consumer”;
- Data vectoring 1 “Data Provider” to 4 “Data Consumer and Provider” and 2 “Data Provider and Consumer” to 4 “Data Consumer and Provider”;
- Data vectoring 4 “Data Consumer and Provider” to 3 “Data Consumer and Provider”;
- Data vectoring 2 “Data Provider and Consumer” to 3 “Data Consumer and Provider”.



(a) **(b)**

Figure 11: The EPM practice and the HDI relationships: (a) EPM targets and electronics devices to data collection; (b) Data vectors to EPM deployment.

The findings raised in this work, supported by the experts' feedback, could implicate the HDI data vectors concerning data collection and use, as well as actors as data providers/consumers – see Figure 12. A deep understanding of this data interaction may potentially lead to the success of the EPM project's implementation.

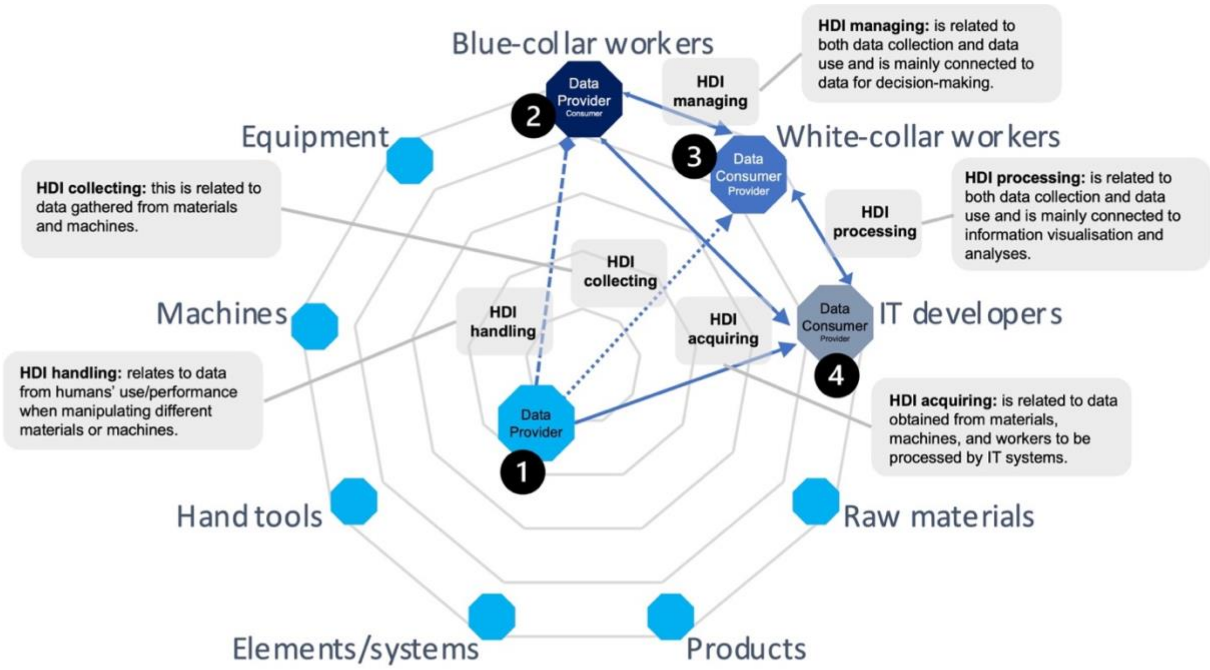


Figure 12: HDI linked to EPM data in Construction 4.0.

First, materials and machines are set as only data providers; in the future, robots may be able to acquire and use data to drive decisions, but this vision was abstracted due to the current on-site reality. The workforce can analyse the data from materials and machines in all dimensions. White-collar workers may collect data from this vector, e.g., amount of hours or kilometres from equipment in use; that vector is named **HDI collecting**. Based on the Theory of Reasoned Action (TRA), it is expected that each person intends to behave (use the data) in a function of their own nature and the subjective norms they are inserted on (Sogani et al., 2005). Warshaw and Davis (1985) defined Behavioural Intention (BI) as a personal conscious intention to perform a specific action in future, and a Behavioural Expectation (BE) is regarding a person's estimation of an act as planned without a strict commitment to perform it. In the case of an EPM deployment at a company, there is a changeable BE of the white-collar workers' actions, as well as their real BI (Warshaw and Davis, 1985). For example, regarding HDI principles, a company (in a top-down EPM deployment approach) should expect from white-collar workers that the data collected will be used to meet the norms and systems provided by the company, avoiding any personal discrimination or punishment. Ajzen (1985; 1991) states that it is possible to predict and justify personal behaviours in known contexts, formulating the Theory of Planned Behaviour (TPB). Using the TPB (Ajzen, 1985, 1991), targeting the white-collar workers who perform the data collection on the company's normative, it is crucial to provide training to raise awareness of EPM & HDI.

Also, blue-collar workers can manipulate those materials and machines performing on-site tasks (and their respective data), establishing the **HDI handling** dimension. In a similar way, the behaviour of blue-collar workers over EPM can be observed through the lens of TRA (Sogani et al., 2005) and TPB (Ajzen, 1985, 1991). Also, the awareness of EPM & HDI practices and, most importantly, the transparency regarding implementing it (e.g., for safety or productivity) may influence blue-collar workers' BE and BI (Warshaw and Davis, 1985). For example, if blue-collar workers are informed that some machine can measure their performance (e.g. welding machine), that can impact their behaviour. Bandura (1977) advocated unifying the theory of behavioural change towards a Self-efficacy Theory (SET), where self-efficacy goals may push individuals' efforts and results (Bandura, 1977). At the same time, Ajzen et. al. (1982) argue that individuals prone to self-monitoring (SMT) can change their attitude-behaviours (Ajzen, Timko and White, 1982). Up to this, the Social Comparison Theory (SCT) drives the individual behaviour of comparing own performance against others (Festinger, 1954). Empowering the blue-collar workforce to self-monitor targeting self-efficacy can drive a bottom-up approach to EPM deployment where those workers can take advantage of data performance for their own benefit (Calvetti, Magalhães, et al., 2020; Calvetti, Mêda, et al., 2020). In that way, blue-collar will be data consumers of their own data provided. The bottom-up "Worker 4.0" concept can put a voice on blue-collar workers to state it: "My work, My data" (Calvetti, 2021). Adding to this, the natural human behaviour of comparing SCT may drive blue-collar workers to be prone to accept EPM. In this, behaviour theories are fundamental to understanding and predicting blue-collar workers' reactions when "handling" EPM. Further perspectives on blue-collar workers' reactions against EPM are more prominent in HDIs' acquiring and managing dimensions.

At the same time, through the **HDI acquiring** vector, IT systems provided by analysts and developers may also acquire data from materials and machines due to the blue-collar workers' performance. In the same way, the **HDI acquiring** vector connects blue-collar workers and IT systems via the sharing of process data. In a scenario where companies provide EPM systems to monitor task performance, workers' reactions against electronic monitoring are captured (Smith et al., 1992; Deane et al., 1995; Kolb and Aiello, 1996; Oz, Glass and Behling, 1999; Alder, 2001). Using EPM with IT in work management can lead to stress due to factors like work overload and the risk of job loss as workers can struggle to meet EPM-enforced standards (Schleifer and Shell, 1992). The implementation of behaviorally-based biometric monitoring systems can be influenced by state anxiety, which may impact typical physiological and performance responses (Deane et al., 1995). This could increase the risk of security challenges, workflow interruptions, and decreased performance (Deane et al., 1995). In this, if the perception of workers is that EPM can be a threat, it gives rise to avoidance and opposition (BI, BE and TPB). Technology Threat Avoidance Theory (TTAT) is about individuals' behaviour in avoiding technology (and information sharing) due to malicious suspicion (Liang and Xue, 2009; Session and Muller, 2022). The Technology Acceptance Model (TAM) adopts the TRA concept that ICT usage is correlated to BI and is mainly driven by the perception of usefulness and ease of use (Davis, Bagozzi and Warshaw, 1989). HDI acquiring diverges from HDI handling in the aspect that the vector of acquiring is permissive to systems data manipulation. At the same time, HDI acquiring diverges from HDI collection due to the possibility of the collection vector not mandatory pursuing a system use. In this, at the HDI acquiring vector, TTAT and TAM are more prominent.

The data processed by the systems will be consumed by the white-collar workers for decision-making, compounding the **HDI processing** vector. Moreover, the **HDI processing** vector data from white-collar workers may be collected. When observing the aspect of white-collar workers as data providers (being monitored), it raises analogues issues and theories than the HDI vectors of collecting, handling and acquiring. Forward, this HDI processing vector is crucial to analysing the issues associated with data manipulation. The GDPR regulates data privacy, and it also addresses employers and employees concerning EPM, e.g., Recital 155 and Article 88, granting mainly to the Member States' working collective agreements local specifications (Calvetti, Magalhães, et al., 2020). A workforce explicitly consent formal document is mandatory (GDPR Art. 7) as it demands a privacy notice of how general and personal data will be processed (GDPR Art. 12-13-14) (Calvetti, Magalhães, et al., 2020). Strong cryptography is essential for secure data exchange and storage, and algorithmic bias must be analysed and avoided (Engin and Treleaven, 2019; Calvetti, Magalhães, et al., 2020). Companies must process performance data over a legitimate interest and discuss data ownership among employers and employees (Rowan, 2019; Calvetti, Magalhães, et al., 2020). Monitoring and surveillance can negatively impact the employment relationship if not properly managed or if there is a lack of trust (Holland, Cooper and Hecker, 2015). The Technology Threat Avoidance Theory (TTAT) is crucial in systems trustfulness. System-based Trust (SBT) refers to trust in how data will be manipulated and used and the respective policies and tools adopted to process the data (Holland, Cooper and Hecker, 2015; Pishdad-Bozorgi and Beliveau, 2016). On the other hand, Cognition-based Trust (CBT) pertains to an individual's trust in the people using the data (Holland, Cooper and Hecker, 2015; Pishdad-Bozorgi and Beliveau, 2016), for example, for management purposes. Both types of trust are essential, and building them starts with the employer valuing trust (Holland, Cooper and Hecker, 2015; Pishdad-Bozorgi and Beliveau, 2016). Additionally, the use and implementation of monitoring strategies can impact the trust between the employee and the employer, thus affecting harmony in the workplace (Holland, Cooper and Hecker, 2015; Pishdad-Bozorgi and Beliveau, 2016). This indicates that the employer is a crucial stakeholder in the EPM process, as the risks to the employer and employee depend on the employer's actions. Finally, trust is a crucial driver for the workforce's acceptance of EPM (TAM) and their respective behaviour against it (TRA, TPB, BI, and BE).

Finally, a data interaction between white- and blue-collar workers will occur in both ways in a schema of provider-consumer, as illustrated by the **HDI managing** vector. However, the main aspect concerning this vector is regarding the use of data/information to manage the blue-collar workforce. Managers and workers may experience tension due to EPM deployment (Oz, Glass and Behling, 1999). Supervisors tend to support EPM more than non-supervisors who believe it harms the workplace (Oz, Glass and Behling, 1999). Additionally, there are differing beliefs on the ability of EPM to reduce malfunctioning behaviours, as well as the necessity to inform employees about monitoring (Oz, Glass and Behling, 1999). Employees in organisations that practice EPM are less reactive to EPM than those without electronic monitoring (Oz, Glass and Behling, 1999). Moreover, women are more inclined than men to believe electronic monitoring reduces malfunctioning behaviours (Oz, Glass and Behling, 1999). Providing thoughtful feedback to employees concerning EPM can significantly improve perceptions of fairness associated with EPM, thus positively impacting both performance and satisfaction (Alder and Ambrose, 2005). Bureaucratic organisational cultures might react favourably to EPM, unlike companies with supportive cultures (Alder, 2001). In supportive organisational cultures, involving employees in system design, monitoring specific teams, and restricting monitoring to performance-related tasks could improve attitudes toward EPM (Alder, 2001). In this case, transparency, previous consent, and trust are fundamental elements of EPM deployment. Once again, all the theories discussed above in the other HDI vectors will be relevant and "tested" when using data/information to manage the workforce. For example, an unfair practice from a manager using EPM data can put distrust (TTAT, SBT, CBT) in all initiatives, thus, impacting all other HDI vectors concerning the theories of TRA, TPB, BI, and BE.

Finally, Figure 13 summarises the analyses of the EPM & HDI vectors and connected theories.

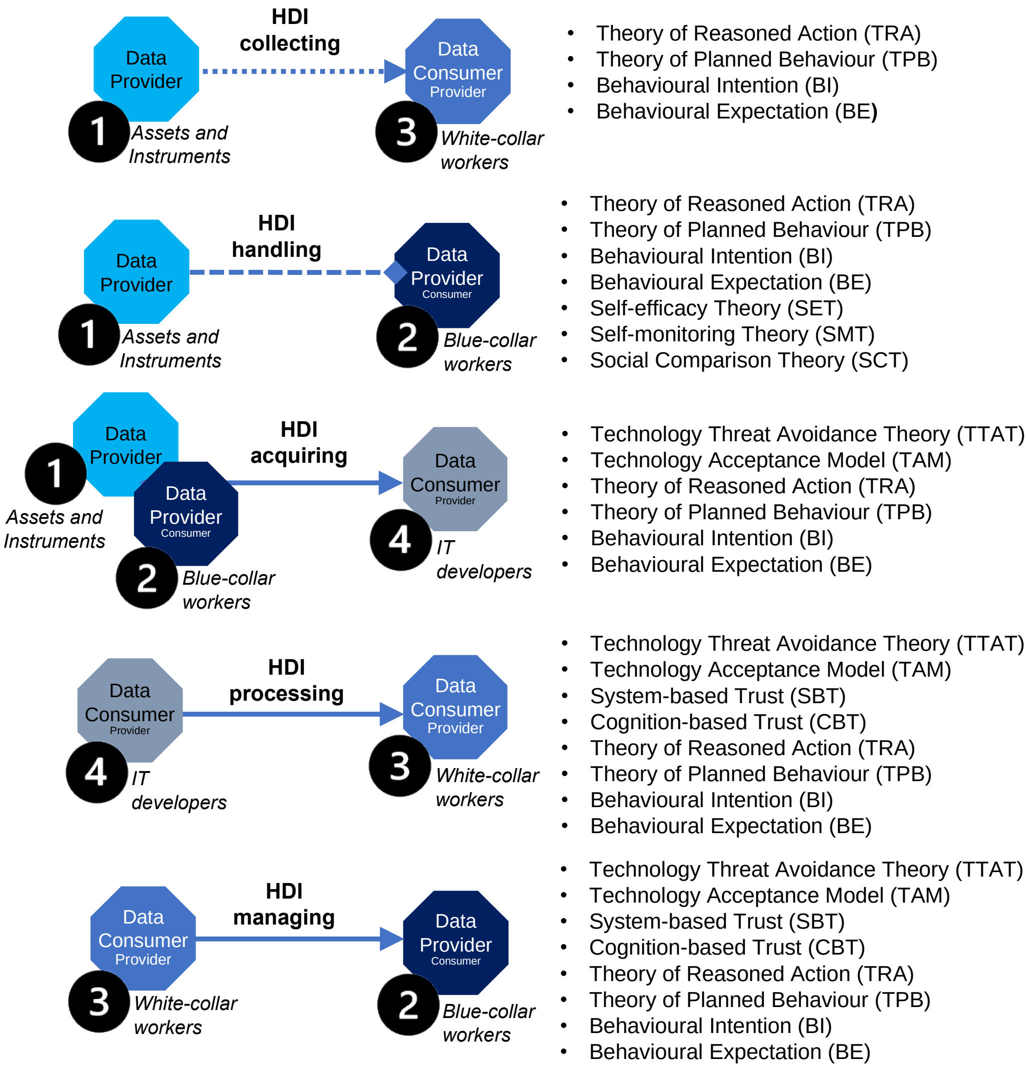


Figure 13: Abduction of Theories linkage with EPM & HDI vectors.

5. DISCUSSION AND CONCLUSIONS

First, based on the conceptualisation of the HDI vectors for EPM practices at the construction sites and the correlated theories and analyses made, it is possible to envisage, through abduction, how HDI may enable EPM deployment (see Figure 14). Regarding an HDI dimension correlated to a TTAT perspective, workers must trust that their data will be manipulated via an unbiased system and managed with good faith by managers. In this, in an environment of EPM-prone acceptance, it is expected a Technology Threat Avoidance Theory (TTAT) (Liang and Xue, 2009; Session and Muller, 2022) is relatively low, whereas System-based Trust (SBT) and Cognition-based Trust (CBT) (Holland, Cooper and Hecker, 2015; Pishdad-Bozorgi and Beliveau, 2016) should be perceived as relatively high. On the other hand, if TTAT is perceived as relatively high, whereas SBT and CBT s should be identified as low, an EPM-prone rejection is expected. At the same time, from an HDI-TPB-connected perspective, an optimistic Theory of Planned Behaviour (TPB) (Ajzen, 1985, 1991) with a prone Behavioural Intention (BI) and Behavioural Expectation (BE) (Warshaw and Davis, 1985) may conducted to an EPM-prone acceptance, whereas the opposite should lead to EPM-prone rejection. Finally, from an HDI-TRA-connected perspective, it is expected to be found in the workforce aspects of Self-efficacy Theory (SET) (Bandura, 1977), Self-monitoring Theory (SMT) (Ajzen, Timko and White, 1982) and Social Comparison Theory (SCT) (Festinger, 1954), leading to action of acceptance of EPM over the lens of the Theory of Reasoned Action (TRA) (Sogani et al., 2005). Differently, if the workforce neglects SET, SMT and SCT, they will probably manifest the action of EPM rejection with a TRA of denying.

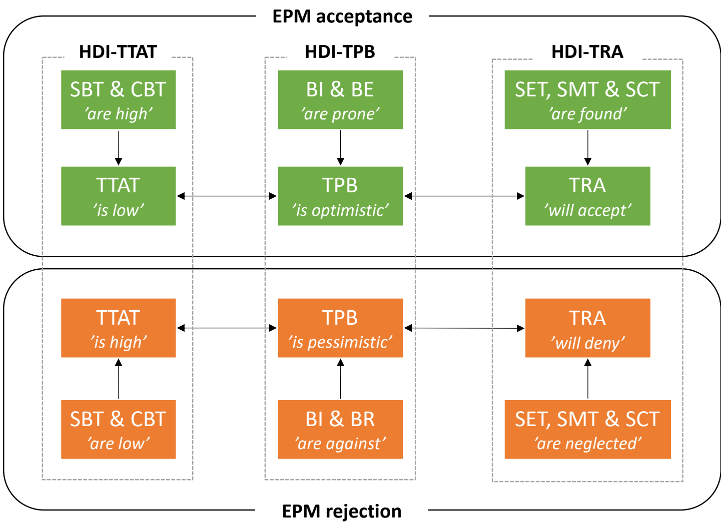


Figure 14: Abduction on EPM acceptance/rejection concerning HDI and behaviours Theories.

EPM is becoming more common in construction sites and can potentially present both opportunities for the project level (e.g., for increased performance and productivity) but also threats to the level of the well-being of the workers themselves (e.g., feelings of being under surveillance, stress, potential GDPR breaches. Considering the research question: "Can the HDI study field improve EPM methods' scalability and feasibility, boosting real case deployments?" the awareness of HDI principles can help researchers to envisage practical outcomes best and be aware of possible barriers. Also, external factors, such as economic or local legislation issues, could impede the scalability and feasibility of EPM methods in real-case deployments. At the same time, HDI processing can support researchers in preventing problems and implementing countermeasures against these factors. HDI concepts raised in this study can support the best understatement of who provides and who consumes the data in sensored construction sites. Also, it highlights that on-site data can be related to a material, a tool or equipment; however, it is handled/operated by a worker who can be profiled. Finally, it delivers a better definition of the roles, such as who will manage the technological aspects in the person of the IT workers. Also, the role of white-collar managers, who will deliver the message about EPM principles and who will manage workers with that information. Very relevant, the blue-collar workers placed as data providers must be wholly informed and trained about EPM. To account for such threats and offer some tools to overcome them, the concept of HDI and all its dimensions (e.g., the role of the stakeholders either providing and/or consuming data) has been developed, originally outside the field of construction; therefore, it would be useful to bring this concept in the context of construction, integrate it with EPM, and analyse the results of such integration to inform a more conscious EPM implementation on-site. When introducing new technologies across borders, it is crucial to account for cultural differences since national cultures are generally stable (Panina and Aiello, 2005). Successful EPM relies on integrating these technologies with the local cultural context, involving locals early in decision-making, and tailoring the EPM features and procedures to fit local conditions (Panina and Aiello, 2005).

Therefore, the purpose of this study has been to combine the previously disconnected concepts of HDI and EPM in the context of construction sites by highlighting the difficulties associated with employing electronic devices to collect and analyse human data. The respective research gap in the integration of the two concepts is highlighted following a scoping literature review on HDI and EPM within construction sites. This was then expanded with empirical work, including a survey among relevant experts and the authors' analysis that synthesised the literature and survey results. This study thus aims to increase awareness of the significance and complexity of the interaction between HDI and EPM when used on construction sites and contribute to the general discussion on the needs, enablers, and barriers for digital regulatory compliance checking for sensitive, human-related data in the context of construction (for example, when it comes to human physiological data and GDPR concerns). When a researcher or a company uses electronic devices to collect data on a construction site, it entails pulling data from an asset, instrument, or workforce; in this case, EPM serves as the tool, aligning with the instrumentalism theory (Fernandez, 2021). On the other hand, the EPM processing of this data using algorithms for decision-making could potentially apply the principles of the theory of technological determinism, where technology is part of the learning and evolving process (Fernandez, 2021).

Particularly, the literature review showed that there is a disconnection between the HDI and EPM concepts in research and practice. At the same time, the construction management field often neglects both themes. In order for that gap to be examined, HDI experts with knowledge of EPM responded to a survey that set EPM targets and HDI barriers and enablers across multiple electronic technologies that can be applied on-site. The data vectoring concerns the stakeholders and their classification as data providers or consumers. Increasing awareness of HDI and EPM taxonomy is relevant and, for example, can allow GDPR compliance actions. Adding to this, the HDI vectoring classification explains the purpose of the innovative projects' deployment and can lead to awareness of suitable requirements. From practical observation, often implementing EPM projects has a target of productivity improvement that is camouflaged as a health and safety purpose, similar to the greenwashing terminology, which can infer a safetywashing approach. It is worth highlighting that the terminology safetywashing was also defined as "the strategic practice of promoting, marketing, and branding of safety practices without full disclosure of negative information to improve the image of the organization" (pag.1) (Ninan and Clegg, 2024). In this case, we redefine the term safetywashing in the context of EPM when it covers real productivity assessment intentions as promoting to employees that it is for safety reasons. Finally, from the perspective of HDI principles of legibility, agency, and negotiability (Mortier et al., 2014; Hornung et al., 2015; Victorelli et al., 2020), undercover purposes avoid conscious acceptability and block fundamental knowledge from the process.

The understanding of the reasons behind the disconnection of HDI and EPM, as well as the frequent neglect of both within construction management practices, can be informed by a theoretical framework of understanding combining sociomateriality (Orlikowski and Scott, 2016) and work sociology (Lindberg and Vingård, 2012). On the one hand, sociomateriality (Orlikowski and Scott, 2008) highlights how practices co-shape technologies, a concept that also applies to digital technologies (Orlikowski and Scott, 2016). Sociomateriality holds that digital technologies' material and social components are intertwined and integrated in real-world applications (Orlikowski and Scott, 2016). Since acts are being carried out through interactions between humans and non-humans rather than solely human attributes, this has an impact on the agency of the actors using digital technologies (Moura and Bispo, 2019). On the other hand, work sociology can inform the idea of using work itself as a unit of comprehending the external elements influencing the workers and their well-being. The whole range of such elements can be included in the work environment (Lindberg and Vingård, 2012) – such as ergonomics, physical strain, noise, chemical emissions, and illumination. In the context of our study, sociomateriality and work sociology are intertwined in that the lack of co-shaping and fragmentation of HDI and EPM can be understood as a managerial problem embedded in the work environment. The demarcated interactions of the actors using the digital EPM devices and relevant data streams affect and are affected by the limited agency of, primarily, the site labourers (especially connected to the usage of the data generated by their own labour); this is further exacerbated by potential neglect for work environment factors connected to the labourers' well-being (e.g., physical strain), as a result of entrenched management and work practices on-site that mostly favour productivity and "getting the job done" – rather than an improved work environment informed by EPM data monitoring the workers' well-being.

Those findings and frameworks can support the body of knowledge across construction-related domains for EPM feasibility studies when HDI concerns are addressed. Nonetheless, some critical concerns can be raised. On the technical level, application programming interfaces (APIs) can present major barriers in the integration of EPM sensors and systems, especially when such an integration is (rightfully) demarcated by concerns about GDPR and the professional's well-being and work environment. Furthermore, the rapid developments regarding automated EPM data processing and compliance checking via AI may mean that such tasks can be performed quicker and in real-time, but can also pose the risk of relying on systems that are not explainable or transparently understood – a danger especially evident in construction sectors with a low level of knowledge or awareness regarding digital and technological innovations. HDI concerns become even more crucial in this case, but they may be sidetracked if a robust framework regulating EPM practices on a higher level (beyond just "good practices") is not in place. Furthermore, on the sociomaterial level, many developments in EPM are often done in disconnection from the experience of the users (workers) that have to implement it. This can impede some kind of knowledge co-creation on productive and fair implementation practices. HDI considerations can offer some guidelines on how there can be a closer entanglement of the development of the respective technologies with the actors using them, but a more planned approach, touching again on the need for regulatory compliance, may be necessary. This may be further highlighted by a need to go beyond HDI conceptualisations to valorise and expand the applicability of the relevant research findings beyond the single example of EPM technologies or even the AEC domain – and in this process, linking HDI as a descriptive concept informed by observations to theories underpinning the integration of humans, technology, and context. Also, connecting EPM & HDI to explanatory theories. A further expansion and rigorous research on HDI implications of sociomaterial and work environment frameworks, only touched upon briefly earlier in this section, can be a major future direction of research.

Further research directions should deeply investigate data requirements and HDI vectors across the multiple electronic device applications discussed (including on-site studies collecting feedback from the relevant stakeholders), as well as instigate an investigation into the critical concerns raised above.

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