

Review

A Comprehensive Review About Human Digital Twins and AI-Powered Wearables for the Oil and Gas Industry

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Abstract

Construction activities within the Oil and Gas Industry present many challenges and inherent dangers for workers. Many current solutions available in the market lack real-time insights and predictive capabilities for proactive decision-making and operational safety. This industry demands robust solutions to enhance safety, improve security, and increase productivity, and this is where Human Digital Twins (HDTs), Wearables, and Artificial Intelligence (AI) play an important role. HDTs aim to create a dynamic digital replica of workers, integrating data from wearables, IIoT sensors, information systems, and any other data source available, enabling continuous monitoring of physiological and cognitive conditions. Complementing HDTs, AI-powered wearables collect enriched data from embedded sensors, such as heart rate, blood oxygen, or fatigue, and integrate deep learning algorithms to predict potential incidents directly on the edge before they happen, thanks to their high computing capabilities. This review represents the state-of-the-art for HDTs and AI-powered wearables for the Oil and Gas industry. It explores current technological developments, their applications, the challenges and limitations of deploying them into a real-world project, and also synthesizes current research and industry practices, highlighting their potential in human health and safety. Additionally, it identifies future research directions to overcome existing barriers.

Keywords: Human Digital Twins (HDTs); artificial intelligence (AI); wearables; Industrial Internet of Things (IIoT); occupational health and safety; edge computing; oil and gas industry



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1. Introduction

The Oil and Gas Industry (O&G) is a critical component of the global economy, as it supplies not just hydrocarbons but also petrochemical products [1]. Each phase of the Oil & Gas Industry's lifecycle, from design to operation and maintenance, poses significant challenges and risks to environments, populations, and personnel. Operating facilities are typically built in harsh environmental conditions; hence, O&G facilities, including refineries, onshore pipeline facilities, offshore platforms and subsea pipelines, etc., require an integrated multidisciplinary approach to deliver these large-scale projects. The tasks in crude O&G exploration, production, processing, storage and transportation must comply with environmental, health and safety, and security regulations [2,3]. The stages of a typical O&G project are depicted in Figure 1, offering unique challenges and opportunities as HDTs, AI-powered wearables, and IIoT devices continue to emerge and become more prevalent

in these environments. This article will review this lifecycle and how these emerging technologies can be used to enhance safety, improve security, and increase productivity.

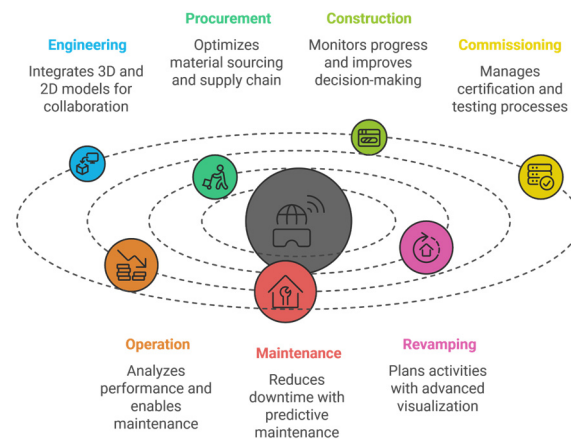


Figure 1. Comprehensive Workflow for the O&G Project Lifecycle.

The O&G industry develops construction projects from a “green field” starting point—often called EPC projects—until commissioning and handover, after which they become projects in O&M and are considered brownfield areas in highly flammable environments. Many of these projects are in remote locations with no communication infrastructure or basic amenities nearby [4]. Once construction begins, it faces unique challenges such as extreme weather conditions or uneven terrain in isolated remote areas [5]. These large-scale construction projects require a massive and diverse workforce consisting of project engineers, managers, helpers, technicians, and many other specialists and supportive laborers. Managing this large workforce presents many safety issues, complex logistical considerations, and detailed planning and coordination challenges [6].

Monitoring safety, efficient progress and supervising on-site construction projects can be more challenging than on O&M sites. Established communication methods and monitoring tools and techniques have limitations on construction sites. Moreover, most monitoring and management systems lack adequate communication technologies for real-time data. There is a pressing need for innovative monitoring tools and techniques to achieve the aims of zero accidents, maximum efficiency, and construction project success in time and costs [7].

To overcome the current limitations, recent technologies can help to create supervision and safety management solutions. The integration of Digital Twins (DTs) [8–12], Artificial Intelligence (AI), the Industrial Internet of Things (IIoT) [5,8,13–15], along with wearables [16–21], has the potential to transform O&G construction sites into what Industry 5.0 coined, a framework for real-time, human-centric decision-making. In order to create an effective supervision system, Human Digital Twins (HDTs) can be developed. They aim to create digital human replicas to track real-time human physiological parameters, as well as human–environment interactions in real time. Supervised HDTs track the physical and behavioral human characteristics, producing large amounts of data for supervisors to monitor the health status of workers, identify safety issues, and assess their work performance.

To enhance the capabilities of HDTs, AI-powered wearables could be used as the primary source of data collection. Additionally, connected devices equipped with multiple built-in sensors such as a camera, GPS, acceleration, gyro, temperature and ambient light, can collect a variety of different data. Machine and deep learning techniques can then be applied to the data collected to identify trends and anomalies and to predict possible incidents before they occur [22,23]. Natural Language Processing (NLP) techniques within

the wearable computing capabilities allow for natural user interaction and instant feedback of their actions.

Advanced IIoT communication technologies make it possible to exchange data between wearables and HDTs and integrate them into supervisory systems to support better situational awareness and enhanced decision-making. In a remote construction site, new IIoT communication technologies, such as satellite communications [24,25], mesh networks [26,27], or LPWAN technologies such as LoRaWAN™, Mioty™, and DECT NR+, enable connectivity even in the absence of an Internet Service Provider (ISP). To enable IoT communication within a construction site, LPWANs are the preferred option, since they offer long-range and low-power IoT communication, suitable for unattended devices installed in remote locations or confined spaces. However, there are also difficulties associated with the connection of these new technologies, such as deployment, security, reliability, and scalability. This paper reviews current work in the creation of Human Digital Twins (HDTs), Artificial Intelligence (AI)-powered wearable sensors and technologies applied within the O&G Industry, specifically during the construction of a plant. This phase has become increasingly complex, with issues related to unsafe working practices, hazardous environments, complex production workflows and dynamic working conditions.

The objectives of this review are:

- A review of current and future HDTs and AI tools, and a consideration of wearable capabilities including those that incorporate Artificial Intelligence (AI).
- Examples of applications, case studies and best practices that demonstrate the impact of advanced technologies in a real project.
- An assessment of the advantages and disadvantages of their use in relation to safety benefits, operational efficiency and effective decision-making under adverse working conditions.
- A discussion of the barriers to technology integration, privacy, acceptance, and other factors that affect the success of technology implementation.
- Suggestions for potential areas for development in the O&G construction sector addressing the challenges and benefits.

The remainder of this paper is organized as follows. Section 2 describes the systematic review methodology, conducted and reported following the PRISMA 2020 guidelines. Section 3 commences with the concept of the Human Digital Twin, reviewing the current state-of-the-art in terms of related components, current uses and future potential, and then details how emerging AI-powered wearable technologies and associated devices can be utilized to establish a Human Digital Twin within the O&G construction industry, explaining how AI processes data under communication constraints. A dedicated section (Section 3.3) then consolidates the applications of HDTs and AI-powered wearables in the O&G industry, including a review of documented deployments reported by major operators. Section 4 discusses the findings, proposing a multi-criteria evaluation framework to compare the reviewed wearable solutions, and highlighting the current advantages and disadvantages of the emerging technologies and their implementation within the O&G construction industry, as well as current challenges and strategies for overcoming them, including future technological innovation, policy and skills training of the future construction workforce. Finally, Section 5 concludes and outlines potential future research directions that can capitalize on the application of these emerging technologies within the construction phase of O&G projects. The paper aims to inform industry practitioners, clients, planners, facilities managers, public authorities, healthcare providers and the wider research community of current technologies and their applications, to encourage positive change and innovation within the construction phase of O&G projects.

2. Materials and Methods

2.1. Research Strategy

The literature search was conducted using four commonly used academic databases and search engines—Google Scholar, Web of Science, PubMed and Scopus—complemented by an AI-assisted discovery tool whose supporting role is described at the end of this subsection. These databases and engines index scholarly articles, conference proceedings and other relevant sources of information that have been reviewed by qualified experts worldwide. Search queries were constructed using Boolean operators, keywords and filters. The primary search query used in this study was: “Human Digital Twins” AND “wearable technologies” AND (“industrial safety” OR “occupational health”) AND “artificial intelligence” AND (“Industrial Internet of Things” OR “advanced analytics”).

Complementary queries combining subsets of the key terms (“Human Digital Twins,” “wearable technologies,” “industrial safety,” “occupational health,” and “artificial intelligence”) were also executed to broaden coverage and to capture studies indexed under partial term combinations.

To complement the traditional database searches, the AI-based research assistant Elicit was additionally used as a supplementary discovery tool. Its role was strictly limited to the identification of candidate literature: suggesting potentially relevant papers based on the search topics, refining keywords for subsequent database queries, and providing preliminary summaries to support screening decisions. Every candidate study identified through this tool was subjected to the same inclusion and exclusion criteria, applied by the authors, as the records retrieved from the conventional databases, and the final selection decisions were made exclusively by the authors. No AI-generated content was incorporated into the manuscript. All candidate studies surfaced by this tool were subsequently located and retrieved through the four databases listed above; they are therefore included in the database record count of the PRISMA flow diagram (Figure 2), and no records were identified through other methods in the sense of the PRISMA 2020 framework.

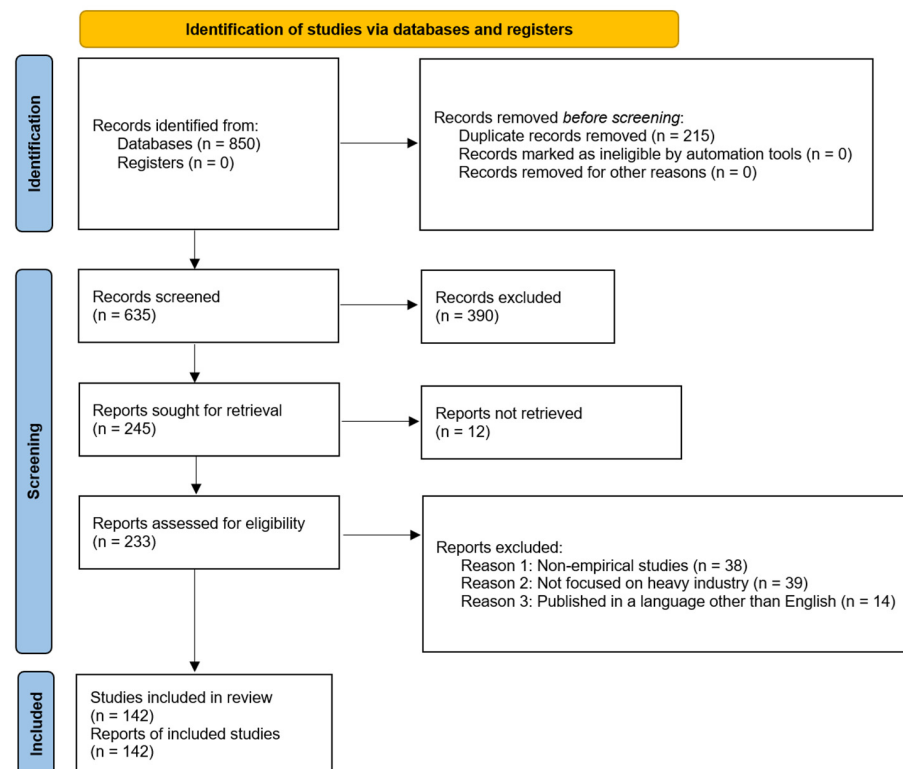


Figure 2. PRISMA 2020 flow diagram of the study selection process.

2.2. Data Collection and Analysis

This review was conducted and reported following the guidelines set by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 [28]. No formal protocol was registered for this review. The database searches were executed between January 2025 and December 2025, in line with the refinement process described in Section 2.3. The review covers literature published between January 2016 and December 2025.

The eligibility criteria were defined as follows:

- Inclusion criteria: peer-reviewed journal articles, conference papers and case studies presenting empirical results, published within the review window defined above, dealing with Human Digital Twins, wearable technology, Artificial Intelligence, or Industrial Internet of Things applications in industrial contexts.
- Exclusion criteria: non-empirical studies (e.g., opinion pieces and purely conceptual papers without original data), studies published in a language other than English, and studies for which no full text was available. Non-empirical sources excluded from the core review could nevertheless be cited for general background and contextualization, as explained below.

A total of 850 records were identified through the database searches. After the removal of 215 duplicate records, the titles and abstracts of the remaining 635 records were screened against the eligibility criteria, and 390 records were excluded. Of the 245 full-text reports sought for retrieval, 12 could not be retrieved, and the remaining 233 were assessed for eligibility. During this phase, 91 reports were excluded based on the established criteria: 38 were non-empirical studies, 39 lacked relevance to heavy industry or the O&G sector, and 14 were published in a language other than English. A final set of 142 studies was included in the core review. These 142 studies constitute the evidence base of this review; the remaining 19 entries in the reference list correspond to sources used solely for general background and contextualization, including methodological guidelines, standards documents, corporate reports and press releases, and they are identified as such where cited. The complete study selection process is detailed in the PRISMA 2020 flow diagram of Figure 2. Records and references were managed using the reference management software RefWorks (ProQuest LLC, Ann Arbor, MI, USA; <https://refworks.proquest.com>, accessed on 5 April 2026).

The papers included were analyzed and grouped by theme. The themes included applications of Human Digital Twins, developments in wearable technology for industry, and challenges to safety in industry.

Given the heterogeneity of study designs and the technology-focused scope of this review, a formal risk-of-bias appraisal using standardized tools was not performed; instead, the provenance and maturity of the evidence—in particular the distinction between peer-reviewed studies and industry-reported deployments—were assessed qualitatively, as discussed in Section 3.3.3.

2.3. Iterative Refinement

The search strategy was refined iteratively, with search terms fine-tuned based on the findings obtained from the initial queries in Google Scholar, Web of Science, PubMed and Scopus, and with keyword suggestions produced by the discovery tool described in Section 2.1 fed back into subsequent database queries, progressively improving the precision of the retrieved results. The aim of this iterative approach was to efficiently identify relevant literature, analyze its content, and distil the key insights applicable to the broader remit of Human Digital Twins and wearable technologies in the O&G construction context.

3. Results

3.1. Human Digital Twins (HDTs)

3.1.1. Definition and Concept

Human Digital Twins (HDTs) are digital replicas of individual humans that reflect their physical, physiological, and psychological characteristics in detail. Keeping the status of an HDT accessible in real time requires the comprehensive integration of advanced digital models with large volumes of data [29,30]. Although the Digital Twin concept was first applied to physical assets and processes within Cyber-Physical Systems (CPS) [31], HDTs extend this paradigm to human beings. Within the context of this review, their main purpose is to preserve workers' health and safety without affecting productivity. To this end, these virtual human replicas gather data from many different sources, such as biometric signals from wearables (e.g., heart rate, body temperature, muscle activity, or blood pressure) and IIoT sensors [32,33]. Figure 3 shows an HDT approach for acquiring, processing, and utilizing data for various purposes, and for developing predictive models that characterize a person and anticipate future states from their current condition.

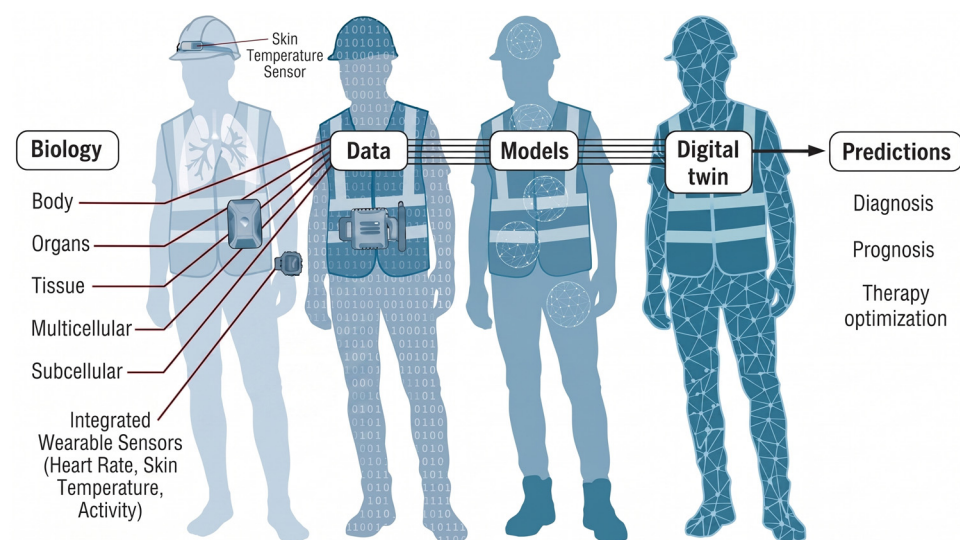


Figure 3. Lifecycle depiction of a Human Digital Twin.

A Human Digital Twin requires several key components for its development and utilization, including data acquisition systems, data integration, modeling, software applications, data processing and analysis systems, and advanced front-end interfaces for a good user experience [34]. Physical sensors such as wearables, smart helmets, or wrist-band sensors capture a variety of physiological signals from workers, including heart rate variability, blood oxygen levels, skin temperature, muscle activity, GPS location, noise levels, gas concentrations, light levels and, more recently, images and video streaming. A software platform processes and analyzes the captured data, integrating all sources through a data integration framework, and assesses health and safety while predicting future outcomes by means of machine learning and deep learning algorithms [35]. Building a digital twin, classic or human, is not new to Industry 4.0; however, HDTs are distinguished from classic digital twins by providing deeper insights into safety and productivity [36]. Moreover, many recent wearable technologies integrate easily with the traditional IIoT ecosystem, allowing a holistic monitoring approach of both workers and workspace in which advanced situational awareness enables managers and supervisors to perceive the environment, comprehend its meaning, and project future actions to promote safety and productivity [29,30,32,37]. On a construction site, this enables projects to be monitored

holistically, combining health-related parameters with the impact of weather, noise, and other environmental factors such as temperature, humidity, or air quality [38–40].

The key difference from the traditional digital twin—used by engineers to optimize the efficiency and reliability of highly predictable physical assets through parameters such as mechanisms, vibrations, temperature, or pressure [41]—is that the HDT focuses on human factors such as physiology, behavior, and cognition, which affect both safety and productivity, especially in hazardous environments under extreme working conditions [29]. Human behavior is far less predictable than that of machines and can be influenced by physical condition, stress, fatigue, exertion, mood, emotions, or resting periods. Many of these factors change rapidly and, in a high-risk environment, such momentary effects can alter a worker's reaction and ultimately lead to an accident. These variables are generated at high frequency, producing massive amounts of data that are difficult to incorporate into models, and therefore demand new ways of sensing, communicating, and recording such signals. Modeling these dynamic human–environment and human–human interactions (e.g., miscommunication or distraction during a task) using adaptive machine learning methods provides new means of analyzing human performance in hazardous, environmentally stressful settings [29].

3.1.2. Benefits and Limitations

The advantages of HDTs are being carefully investigated, with a primary focus on improving safety and increasing productivity during construction [30,32,42]; however, their deployment also involves challenges that must be considered [43]. Their most notable benefit is improved monitoring and prediction: wearable sensors capture physiological and environmental data in real time [29,40], allowing HSE hazards to be identified before they become serious, while hazard simulation and prediction on O&G construction sites contribute to workers' well-being and performance [44,45].

From the construction perspective, HDTs can increase productivity and improve resource management throughout the project life cycle [43,46], enabling supervisors to maintain production while keeping workers healthy by assigning tasks appropriate to their current fatigue and cognition levels [47–50], and to track workers' location and status throughout the day to plan dynamically and meet schedules.

The collected information also allows supervisors to monitor site conditions and act accordingly, facilitating proactive safety management [29,39,42,51]. Increasing research applies machine learning to wearable data to identify early signs of fatigue, heat stress, and dehydration [52], so that work can be distributed more efficiently, enhancing productivity while preventing overexertion [53–55]. Monitoring parameters from multiple sources enables the detection of worker discomfort or stress and of environmental changes [56–59], and early warning systems improve intervention response times, reducing the severity and occurrence of accidents [60–62].

Despite these benefits, significant barriers hinder adoption. Data privacy and security are major concerns, as HDTs increasingly collect personal physiological and behavioral information [63,64]. Workers, already under pressure to perform quickly, may feel under surveillance, inducing additional stress and resistance to technology adoption [42]; workers' acceptance antecedents also significantly influence their adaptation and coping behavior, predicting the extended use of Wireless Sensor Devices (WSDs) [65].

Adoption is further limited by the complexity of implementation and integration on site: modeling an accurate human figure and integrating building information models and monitoring systems with realistic behavior models requires high interoperability between systems and devices [43], and the technology is not always mature enough for strict real-time applications. Other critical factors are the high initial investment, the

maturity of advanced sensor technologies, the need for powerful data processing and skilled personnel [34,66], and the high maintenance costs of the hostile O&G construction environment. Figure 4 summarizes the benefits and challenges of HDTs.

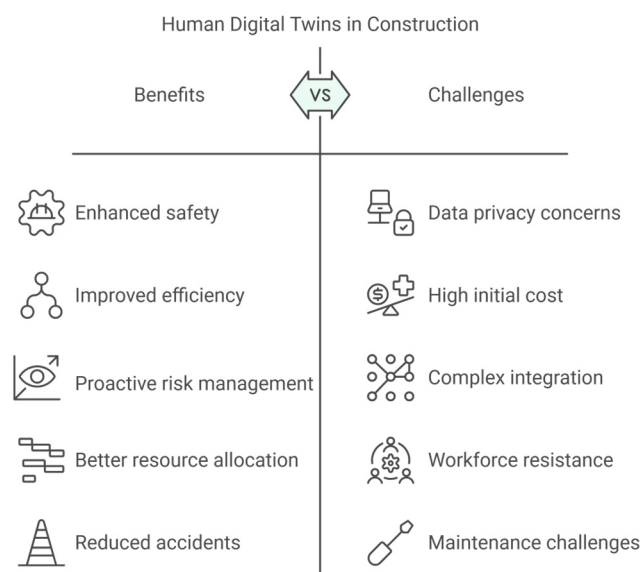


Figure 4. Summary of the Benefits and Challenges of Human Digital Twins (HDTs) in the Construction Phase of O&G Projects.

3.2. AI-Powered Wearables

3.2.1. Overview of Wearable Technology

Wearables refer to electronic devices worn on the body as part of clothing, accessories or items such as helmets, wristbands or lanyards. They can continuously monitor a user, gathering real-time physiological and environmental data as well as the user's location [67,68]. This technology is already utilized in high-risk industries such as O&G, with devices like smart helmets, biometric wearables, smart vests or augmented reality glasses; however, it is still mostly limited to data collection and monitoring.

While traditional safety wearables can only track and record signals from sensors such as the accelerometer and gyroscope, connected wearables with AI-powered capabilities can process the data in real time on the edge and alert the worker accordingly, predicting and optimizing both safety and operational efficiency [50]. For example, instead of simply monitoring heart rate, an AI-powered wearable can analyze heart rate variability to detect early signs of fatigue or forecast exposure risks.

In the O&G industry, these devices can monitor worker health, track location in high-risk environments [69] and detect exposures such as chemicals or heat; workers receive feedback and alarms on their wrist, and supervisors stay in touch through the same device. AI can also support predictive maintenance, anticipating equipment failures and scheduling interventions to prevent downtime, communicated directly to the wearables [70]. Wearables providing real-time location, edge decision support and remote health monitoring are of particular interest [71]; however, implementation faces challenges such as hazardous environment, existing infrastructure, workforce acceptance, and adoption by management and government agencies [72].

Many types of wearables have been proposed for industrial use, from off-the-shelf fitness trackers and biosensors to specialist devices such as smart helmets [73–75], bio-sensing-embedded clothing [72], AR smart glasses or smart safety harnesses. Figure 5 illustrates this new generation of personal protective equipment (PPE), which improves worker safety and helps management to boost productivity, reduce risk and save money [76].

Smart helmets assist with lone-worker tracking, impacts, drops, man-down alarms or weather sensing. AR glasses can be used during training and at work [77] to display operational data, diagrams or safety information while keeping both hands free [72]. Sensors in safety vests capture heart rate and respiratory activity to detect heat stress and ergonomic exhaustion from extreme postures [78,79], smartwatches record movement and exertion and alert when fatigue limits are exceeded [80], and smart harnesses detect incorrect use or absence when needed.



Figure 5. Illustration of wearable technology used for data collection.

These devices can operate in remote locations, withstand rough conditions and even support medical assessment before help arrives, forming an essential part of advanced situational awareness for workers, management and other stakeholders [81]. This is critical in offshore oil rigs, mining operations [82] or O&G large-scale construction sites, where geolocation allows rescue services to track an affected worker, improving emergency response times and potentially saving lives.

Biometric data is processed on the edge by embedded AI algorithms to identify anomalies [83], predict risks [50] and provide real-time insights: a worker wearing a smart suit could be alerted to a potential heatstroke and advised to move to a cooler location [84], while other solutions prevent injuries before they occur using machine learning and predictive analytics [85]. Wearables can also be integrated with maintenance management software, a digital permit-to-work system, or other IIoT technologies in the wider plant ecosystem, connecting worker, activity, environment and the safety officer in charge [86].

Technically, industrial wearables are shaped by the balance between computational power, power consumption, durability and real-time constraints, which must be aligned with operational necessities [74]. Edge computing processes data immediately within the device, avoiding cloud latency and enabling timely decisions in safety-relevant environments. Miniaturization makes recent devices lighter, more robust and more ergonomic without sacrificing functionalities [67], but limited battery runtime still hampers wide adoption in remote workplaces; hence, energy-efficient sensors, communication such as Bluetooth Low Energy or LPWAN, and energy-harvesting approaches have become increasingly common. Devices must also withstand varying temperatures, humidity, impacts and general wear, so robust materials and rugged solutions are critical [65,68,69]. Altogether, wearable technology is fast becoming a key enabler to improve safety, productivity and health in industrial environments, allowing risks to be identified and mitigated before they cause damage.

3.2.2. AI in Wearables

Although there are multiple definitions of Artificial Intelligence (AI), all have in common that it is the field of computer science focused on creating machines capable of performing tasks that typically require human intelligence, like learning, reasoning or problem solving, identifying patterns in data to make decisions without being explicitly programmed [87–89]. Embedding an AI model in a wearable presents challenges derived from limited computing capabilities, power limitations and reduced form factors, so the models must be properly trained and very specific to their activity. Nevertheless, current AI-enabled wearables can process considerably large amounts of data and provide immediate results to enhance worker safety, productivity and well-being [50,90,91].

AI can be deployed on the edge when instant low-latency analytics for immediate decisions are needed [91–95], or on the cloud for complex long-term analysis of vast amounts of data from multiple devices using the computing power of data centers [93,96,97]. Some companies take a hybrid approach, performing simple tasks on the edge and long-term trends in the cloud [93,98]. When a health risk requires immediate attention and the device may not be connected to the Internet, edge AI makes the decisions locally; on-cloud AI, in turn, gathers the data streamed from wearables and IIoT sensors to analyze historical trends and build an overall risk model to improve worker safety.

Figure 6 presents the hierarchical structure of AI in wearables, where Machine Learning (ML), Neural Networks and Deep Learning (DL) appear as the key technologies for time-critical decisions and predictions on the edge and context-aware solutions [99].

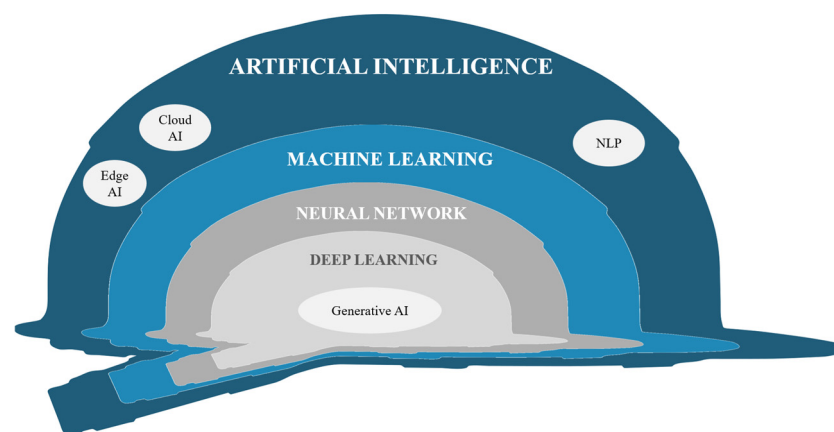


Figure 6. Overview of Artificial Intelligence and its Subsets for wearable devices.

Machine Learning (ML) enables wearables to learn from data and improve the accuracy of future predictions and classifications over time [100]; many analyses in the literature utilize it to find patterns in worker behavior and physiological signals that indicate health risks such as fatigue and stress [101]. Deep Learning (DL), a subset of ML based on “deep” artificial neural networks [102–104], detects events such as a fall or an unsafe working condition and identifies anomalies in a worker’s movement that indicate fatigue [52,105], being very efficient at dealing with high-frequency sensor information and extracting patterns not discoverable by other methods [106]. Natural Language Processing (NLP) [107] supports voice commands for hands-free interaction with devices [72], can warn workers about particular situations and generate alternatives [108], and a rule-based approach, NLTK, has been employed to identify hazards from construction accident narratives for risk prevention [109].

The implementation of AI in wearables for hazardous environments could leverage several innovative applications [50,110,111]. Machine learning processes large volumes of sensor data on the edge, preventing network congestion [106], and turns massive physio-

logical and environmental data into insights for workers and supervisors [93,112]. They can also analyze worker behavior to identify increased stress levels [113], fatigue and exposure to health and safety risks [52,101], alerting, for instance, to heat stress before it causes serious harm. Heart rate (HR) is widely used as an indicator of fatigue and stress but is not sufficiently reliable on its own [52,114], so measures such as skin temperature and movement are combined with it to identify early signs of heat stress in workers [115].

AI also improves accuracy in health monitoring and predictive analytics [86]: predictive models built from work history can detect early warning signs such as a sharp increase in heart rate, loss of balance or even indicators of Parkinson's disease, triggering a warning in time to prevent an incident [115].

There is much research about AI applied to industrial settings: improving sustainability in the production part of the O&G value chain [116], autonomously allocating resources with deep reinforcement learning [117], maximizing production and Ultimate Oil Recovery in reservoir management [118], optimizing quality and safety of well construction through smart drilling [119], enhancing maintenance logistics on offshore platforms [120], or applying AI to seismic imaging in exploration to increase resource discovery [121]. In other industries, AI is used to improve energy efficiency [122], where the challenges have shifted towards integrating new, complex data types and meeting policy goals [110].

3.3. Applications of HDTs and AI-Powered Wearables in the O&G Industry

Having reviewed the enabling technologies in the previous sections, this section consolidates the applications of HDTs and AI-powered wearables that are specific to the O&G industry, with particular attention to the construction phase of O&G projects. The applications are grouped into two complementary perspectives: applications driven by the Human Digital Twin as the integrating platform (Section 3.3.1) and applications delivered by AI-powered wearables integrated into workers' personal protective equipment, which act as the main data source of the HDT (Section 3.3.2). Finally, Section 3.3.3 reviews documented deployments of these technologies by O&G companies, together with the current maturity of the available evidence.

3.3.1. HDT-Based Applications

In the O&G industry, construction and safety teams have differing priorities: construction departments aim to build the asset as efficiently as possible to meet deadlines, while safety departments seek to complete the work without posing risks to people. The pressure to increase productivity and reduce costs makes this balance difficult; a National Safety Council survey of 2000 U.S. workers found that 33% believe their employers prioritize productivity over safety, a proportion that rose to 60% among construction workers [123]. Since productivity remains essential for economic feasibility, a growing number of companies are adopting HDTs for simulation, prediction, and real-time tracking of physiological conditions, recognizing their potential to enhance safety and productivity simultaneously [66]. The following applications illustrate how HDTs based on AI-powered wearables can benefit both.

Productivity and Resource Optimization

HDTs can track work activities, worker movements, and resource utilization in real time, enabling managers to plan and optimize workflows and schedules, forecast material requirements, and anticipate where additional plant or labor will be needed [124]. Integrated with other digital twin systems, they can simulate scenarios to increase construction efficiency [36,38,39,125]. Sharing and analyzing these data among project stakeholders further improves decision-making; a non-peer-reviewed industry report suggests that digital twin technology can improve project scheduling by 28% with significant cost savings [126];

however, this figure has not yet been validated by independent peer-reviewed studies. HDTs are also increasingly used to optimize the permit-to-work (PTW) system, ensuring that only authorized and trained personnel perform a given task [127,128].

Task Allocation Based on Physical Condition and Trainings

HDTs also enable task allocation based on the monitored health and well-being of workers, assigning the right person to the right task at the right moment. Wearables detect, for instance, rising fatigue levels that could put the worker or others at risk [16–18], while the system verifies the appropriate training and certification for the task [46], avoiding overexertion and minimizing accidents [47,48]. Combining historical and real-time data, the HDT applies AI-powered predictive models to identify early risks to a worker's health [50], for example, prompting management to schedule a rest period for a worker at risk.

Environmental Monitoring

HDTs can incorporate sensors that gather real-time data on temperature, humidity, air quality, wind speed, gases, or UV radiation [56], alerting personnel when conditions turn dangerous so that action can be taken before harm occurs [57]. Examples include warning of a worker's exposure to an extreme heat index, informing of detected toxic gases [58], or halting lifting and crane operations under unsafe wind [59]; heat alert thresholds can be aligned with established occupational exposure criteria such as the NIOSH recommended standard for heat and hot environments [129]. Combining historical data from sources such as weather stations, HDTs can apply predictive analytics to anticipate risky conditions [84,114] and engage safety measures in advance, as well as plan tasks to avoid overheating, distribute workload, and provide cooling and healthy lighting for short-term comfort and long-term sustainability [130].

Stress Management

Employee stress and fatigue can be monitored using wearables combined with time-frequency analysis techniques [29]: Heart Rate Variability (HRV) and bispectrum-based features allow a rapid assessment of mental or physical stress [131], while monitoring heart rate, electroencephalography, skin temperature, or repetitive motion can assess fatigue [132]. Machine learning and deep learning are being explored to detect stress directly on the edge from signals such as electrodermal activity, heart rate, acceleration, and video [113,133]. Emerging approaches such as Empathic Large Language Models [134] and extended Human Asset Administration Shells [135] can support individualized mental health assistance and cognitive load management; stress in human–robot interaction has also been studied [136], together with technologies supporting interventions such as cognitive behavioral therapy, balanced against screen time and cyberbullying concerns [137].

Incident Identification and Emergency Response

HDTs enable the real-time detection of anomalies in worker conditions and environmental factors, generating immediate feedback from wearables, environmental monitors, and IoT devices to respond to unfolding problems [38], for example, by rescheduling work to avoid hazardous conditions. When a risk is detected, HDTs can immediately trigger evacuation, alert emergency services [138], and track workers in real time to guide them to the nearest muster or assembly point [69,139]—a crucial capability, since an accident can stop work and severely impact the project economy. Following an incident, HDTs provide records of the context (environmental conditions, work permits, or vehicle information) just prior to the event [140], supporting root cause analysis and lessons-learned systems that identify failures [60] and their contributing factors to prevent recurrence [61]. Predictive analysis can further identify future risks [62], such as repeated failures or correlations

between site factors and incidents, informing decisions on safety practices, maintenance scheduling, or worker assignment during peak danger periods.

3.3.2. AI-Powered Wearables as Smart Personal Protective Equipment

The integration of AI-powered wearables in Personal Protective Equipment (PPE) can make a significant positive difference to safety, efficiency and productivity in the Oil & Gas industry. These PPE wearables increase safety and productivity by leveraging real-time data to monitor the surrounding conditions in a project, creating an enhanced situational awareness solution. Table 1 highlights the list of wearables that can be used for the construction of O&G-related infrastructures as part of safety PPE.

Table 1. PPEs. This table outlines the primary categories of AI-powered wearable personal protective equipment (PPE) utilized in O&G construction environments. It highlights Smart helmets, Smart vests, Smartwatches, Smart Ear Protectors, Safety Glasses, Smart Harness, and Smart Shoes.

Type of Wearable	Benefits and Monitoring
Smart Helmets [139,141–145]	They can detect impacts, falls and other potential safety hazards and can be connected to IIoT networks for instant alert to the supervisors. They can also be equipped with gas detectors for hazardous environments, barometric sensors for working-at-height detection, panic buttons for emergencies, and temperature and humidity sensors for heat stress detection. These helmets can also incorporate Global Navigation Satellite System (GNSS), Bluetooth Low Energy (BLE) and Ultra-Wideband (UWB) location technologies to provide an immediate and quicker response to emergencies and pinpoint exactly where the worker is at the moment of the alert. Smart helmets can prevent workers from accessing a hazardous area if they are not certified or trained to do so. The wearable device constantly monitors workers' locations and the environment around them. Real-time communication with supervisors during critical situations is also enhanced.
Smart Vests [139,146,147]	Wearable biometric devices with built-in bio and motion sensors can measure heart rate, body temperature and fatigue and automatically detect risk of heat stress or early signs of exhaustion. They can trigger alerts directly to medical staff when needed and optimize task assignments to ensure safe working conditions by monitoring physiological status of workers during those specific intense physical tasks, potentially helping to increase productivity.
Smartwatches [29,139,148–150]	They can track activity patterns, location, heart rate variability, blood oxygen, temperature, and current models can even detect many more parameters. They can automatically alert supervisors and frontline workers that are under critical fatigue levels. Scheduling plans can be enhanced with this solution to optimize workflows and ensure staff are taking timely breaks. These solutions can also incorporate a camera to take a photo of an incident or observation as evidence, act as an IIoT gateway device to collect other worker devices signals and send them back to the control room for processing and analytics, manage work permits anywhere and anytime, and scan worker devices to retrieve their digital passport with their respective personal data, latest medical information, full training history, active permits, and current tasks assigned.
Smart Ear Protectors [139,151,152]	They ensure adequate protection levels against hearing damage from excessive environmental noise. These noise monitoring systems can be linked to the hearing protectors, allowing the system to adjust protection levels while at the same time ensuring that the user receives just the right amount of attenuation. Other audio features have been incorporated into hearing protection systems to improve team communication. In increasingly noisy working environments, these systems have become a vital safety feature for workers. The systems provide clear natural audio, allowing workers to hold conversations with their colleagues without restriction. The overall effect of these systems is to help improve safety, and to create a safer, more dynamic and more productive working environment.

Table 1. *Cont.*

Type of Wearable	Benefits and Monitoring
Smart Safety Glasses [153–157]	Project data, plans, workflows and safety information can be overlaid in real time into the field, improving accuracy and safety. These solutions allow workers to complete tasks whilst hands-free and fully aware of the working environment, reducing the potential for error. The software integrated into the AR glasses can use the built-in cameras to recognize a series of events, including PPE non-compliance, proximity to hazardous or in-operation machinery, intrusion into a restricted or prohibited area, missing barricades when operating machinery, people under lifts, missing barricades when working at heights, lone workers, a fallen worker, full or overflowing bins, unauthorized parking, presence of a banksman, poor visibility and camera tampering. It can also count the number of workers in a field.
Smart Safety Harnesses [139,158]	They ensure correct usage of the working-at-heights harness and real-time safety compliance with a detection system. They can detect misuse of the harness during usage and alert for real-time compliance during construction activities or any other hazardous task where extra protection is required.
Smart Shoes [76,139,159]	They allow tracking of posture, pressure (to determine heavy loading), and ergonomic movement. These safety shoes can automatically prevent musculoskeletal injuries, alert unhealthy walking patterns and identify hazardous ground conditions to keep workers safe and productive without putting them in excess fatigue.

3.3.3. Documented Deployments in the O&G Industry

Beyond the potential applications described above, major O&G companies such as Saudi Aramco, BP, Chevron and Shell are already integrating these solutions to mitigate risk, reduce cost and maximize value in their operations. It should be noted from the outset that the deployments described in this subsection are documented primarily through corporate communications and industry publications [124,160,161] rather than through peer-reviewed studies, and they are presented here as evidence of industrial adoption rather than as validated scientific results. Saudi Aramco, for instance, has developed the Smart Resources Management System, which supports O&G development and production by using AI solutions, wearables, IoT technologies and big data analytics to optimize resource allocation and enhance operational safety [124]. BP's digital transformation initiatives aim at mitigating risk offshore to protect its workers and the environment by leveraging wearables and digital twin technology, and Chevron similarly applies digital twin technology to optimize the performance of its assets [160]. Similarly, Shell's Smart Construction initiatives use IoT technologies such as wearables to track workers' productivity in real time at construction sites, preventing accidents and enhancing construction safety [161].

Adoption is greater in regions with more mature industrial bases, such as the Middle East, North America, Europe and parts of Asia-Pacific, where governments provide incentives for these emerging solutions and increasingly stringent regulatory environments push operators and contractors towards digital solutions to remain competitive. In summary, the evidence reviewed in this article can be grouped into three tiers of maturity: (i) peer-reviewed empirical studies, which constitute the 142-study core of this review and support the technological capabilities discussed in Sections 3.1 and 3.2; (ii) peer-reviewed conceptual and review literature, used for framing and background; and (iii) industry-reported sources, such as the corporate communications and pilot projects cited in this subsection, which document adoption but have not undergone independent, peer-reviewed evaluations at full scale. Reported benefits in safety and productivity from this third tier are therefore promising but still preliminary, and further studies measuring the impact of HDTs and AI-powered wearables in real O&G construction projects are needed to consolidate the evidence base.

4. Discussion

The construction industry for O&G plants is changing fast, with new digital technologies emerging for HDTs, AI wearables, and other IoT devices and sensors that are being integrated to create an IIoT environment. This is bringing a new wave of benefits for professionals working in hazardous, challenging and remote environments towards achieving greater safety, efficiency and sustainability. These factors are influencing the integration of new tools and methodologies to support better asset management in the global market. Several factors are at play, including workforce adoption, technological innovations and site-specific requirements. The main drivers for adoption are increasingly stringent environmental and safety regulations.

4.1. Evaluation Framework for AI-Powered Wearable Solutions

To effectively assess the suitability and overall value of the AI-powered wearable solutions detailed in Section 3, it is necessary to establish a standardized evaluation framework. Building upon the predictive lifecycle of the HDT presented in Figure 3 and the technological capabilities outlined in Table 1, we propose a multi-criteria evaluation matrix in Table 2, tailored to the specific demands of O&G construction environments. The proposed framework evaluates each wearable technology against five core criteria:

- **Safety Enhancement Potential:** The ability of the device to capture critical physiological or environmental data, perform edge computing for anomaly detection, and prevent accidents or health emergencies (e.g., heat stress, falls, gas exposure).
- **Operational Efficiency & Productivity:** The device's contribution to workflow optimization, real-time task allocation, and reduction of operational downtime.
- **Implementation Complexity:** The technical difficulty associated with deploying the device, including integration with legacy IIoT infrastructure, data processing requirements, and communication network dependencies.
- **Worker Acceptance & Ergonomics:** The likelihood of workforce adoption based on comfort, weight, ease of use, and intrusiveness regarding data privacy.
- **Environmental Resilience:** The device's durability, ruggedness, battery life, and ability to operate continuously in the extreme conditions typical of O&G sites (e.g., extreme temperatures, dust, explosive atmospheres).

Table 2. Evaluation Matrix of AI-Powered Wearable Solutions for O&G Construction.

Wearable Technology	Safety Enhancement Potential	Operational Efficiency	Implementation Complexity	Worker Acceptance & Ergonomics	Environmental Resilience
Smart Helmets	High	Medium	Medium	High	High
Smart Vests	High	Low	Low	Medium	Medium
Smartwatches	Medium	High	Low	High	Medium
Smart Ear Protectors	Medium	Medium	Low	High	Medium
Smart Safety Glasses	Medium	High	High	Low	Low
Smart Safety Harnesses	High	Low	Low	Medium	High
Smart Shoes	Medium	Medium	Low	High	High

To support selection of the most suitable solution, each wearable technology has been evaluated against a set of key criteria reflecting the priorities of an O&G operation. No single solution meets all scenarios but overall, the Smart Helmet offers the most well-rounded solution for use within the O&G industry. This form factor provides the highest level of environmental resilience and safety enhancement, as it is offered as a universal PPE (Personal Protective Equipment) item that is already widely accepted and mandatory for all O&G workers. As might be expected, Smartwatches and Smart Ear Protectors offer low implementation complexity and high worker acceptance and provide

improved operational efficiency through enhanced communication and streamlined PTW (Permit-to-Work) management; however, both of these solutions suffer from reduced environmental resilience when compared to the Smart Helmet. In terms of enhanced operational efficiency and remote assistance of workers, the Smart AR Glasses have huge potential, with their ability to overlay project data onto the real world that the worker can view while focusing on the task in hand. However, current assessment reveals that there is a high implementation complexity of AR-enabled wearables, with many having environmental fragility and low battery life, causing worker visual obstruction and resulting in a number of ergonomics discomfort issues that can quickly become apparent over long work shift periods. Therefore, a hybrid approach is proposed to support the proactive safety management goals of Industry 5.0 and, more generally, for comprehensive HDT deployments in the O&G industry. Information from the most resilient wearable (Smart Helmet) can be fused with information from the most efficient interface (Smartwatches).

4.2. Benefits

Human Digital Twins, AI-powered wearables, and related innovations are gaining momentum across the O&G sector as a means to enhance safety, improve productivity, and boost efficiency, and O&G companies are among the early adopters of these solutions, as the deployments reviewed in Section 3.3.3 illustrate. These digital solutions are expected to find their greatest adoption at high-risk O&G construction sites, where real-time data, timely insights, and predictive analytics can contribute both to protecting workers and to preventing avoidable downtime and losses. Building on those documented initiatives, some of the industry trends related to human-centric technological innovations are presented hereunder.

- **Integration with Digital Twins:** As construction information is being created in a new digital format, the construction digital twin is becoming a highly detailed digital model of a building or construction site [10–12]. Every physical and digital asset, and even the construction workers, can be included in the model. The digital twin allows for real-time monitoring and maintenance of assets to enable predictive maintenance. Additionally, different scenarios can be simulated, which allows for virtual testing of processes, and if things could go wrong, they can be identified beforehand. Processes and decisions can be optimized for increased efficiency in the construction industry. In the O&G industry, the digital twin model enables precise lifecycle tracking of the assets. It makes it possible to manage resources and personnel more effectively throughout the entire construction process. The digital twin also supports proactive safety processes to meet the special conditions of an oil construction site [36,38].
- **Integration with IIoT:** HDTs and wearables have been utilized within IIoT environments, allowing data to be shared and real-time monitoring of site activity to take place [8,15]. By collecting and sharing large datasets across various sources, construction professionals can utilize predictive insights to identify potential failures of equipment or health risks to workers before they become major problems [70,71]. IIoT also shows how energy is being used on site most efficiently and provides insights to construction professionals, allowing them to work more efficiently on site, maximizing productivity whilst reducing environmental impact.
- **Focus on Worker-Centric Solutions:** Industry 5.0 is a human-centric revolution [29,30]. Going forward, wearable solutions need to be light, comfortable to wear, and easy to use. Usability and ergonomics are essential design factors when developing wearable solutions that need to seamlessly integrate into workers' workflow [74,79].
- **Advancements in AI and Machine Learning:** Breakthroughs in AI and machine learning are unleashing greater value from wearables and digital twins. By analyzing

complex patterns in real-time data, AI identifies key insights that matter most and delivers them to the right people at the right time. It can predict when an employee is at risk of fatigue, when an incident is most likely to occur, and what the optimal levels of inventory and resource allocation are [52,101]. Continued advances in machine learning algorithms are expected to yield increasingly accurate and effective safety strategies and workflows.

- **Sustainability and Green Construction:** As sustainability requirements tighten, digital technologies and wearables are increasingly being used to track carbon footprints, ensure compliance with green building codes and reduce waste on construction sites [116,122]. Developers can track their progress toward sustainability goals in real time, following energy and materials in relation to environmental and budgetary consequences, and make changes on the fly to lower costs and environmental impact.
- **Interoperability and Standardization:** The importance of interoperability and standardization of protocols and frameworks for integration of systems, devices and platforms is increasingly recognized [34,43]. Standardization on a few protocols can simplify integration of systems and devices within an organization and facilitate adoption of new technologies by improving collaboration between different systems and devices.
- **Remote Operations and Monitoring:** Many of the technologies that enable remote operations and monitoring have matured to the point where they are key to delivering construction projects safely and cost-effectively. Camera-enabled live monitoring of the site and drones capturing aerial images over time are now common practice [68,71]. However, developments are also enabling live remote construction supervision using wearable cameras, which are becoming increasingly common. Live footage can be monitored by supervisors in a remote control room, and operatives on site can be asked questions and instructed with key frames from selected footage, with AR markers added to the images to provide guidance [154,156]. This all means that project managers can safely manage more sites at the same time, reducing the on-site team required to deliver a project and ensuring that best practice methods and construction health and safety protocols are being followed.
- **Enhanced Training and Simulation:** It enhances workers' training using advanced virtual and/or augmented reality environments [77,108]. These training environments will incorporate wearables and enable workers to complete tasks in an immersive training environment to enhance learning. Realistic virtual tasks, routine and emergency maintenance tasks, and work at elevated heights can be simulated to enable the worker to complete many more training sessions in a safe and risk-free environment before performing the actual work on site.

4.3. Challenges

The adoption of new technologies such as Human Digital Twins (HDTs), AI-powered wearables or IIoT devices in the O&G industry brings many benefits, but several challenges as well. From technical, organizational and cultural perspectives, all of the challenges are affecting the pace, cost and effectiveness of a solution while it is deployed and operating in a project. Table 3 groups these challenges by category with proposed solutions. The following sections detail the main categories.

Table 3. Summary of Challenges and Proposed Solutions for Implementing Advanced Technologies (HDT, AI wearables, IIoT) in O&G Industry. This table details the challenges encountered and proposed solutions for implementing HDT, AI wearables, and IIoT solutions.

Challenge	Subcategory	Description	Proposed Solution
Technical Challenges	Readiness of Technology	Current technology is not mature enough for specific O&G challenges.	Innovations in AI, sensors, and materials science to address limitations.
	Integration Complexities	Difficulty integrating advanced tech with legacy infrastructure.	Careful planning, collaboration with providers, and tailored solutions.
	Data Security and Privacy	Heightened cybersecurity risks due to data transmission.	Implement robust security protocols for data integrity and confidentiality.
	Infrastructure Limitations	Lack of robust networks and power supply in remote locations.	Invest in communication and energy infrastructure.
	Scalability Issues	Challenges in expanding tech to large-scale operations.	Optimize costs and ensure performance during scaling.
Cultural and Organizational Barriers	Workforce Resistance to Change	Resistance to new tech due to fears or lack of familiarity.	Employ change management strategies and inclusive planning.
	Management Hesitation	Reluctance to invest due to ROI uncertainties.	Build strong business cases with data and success stories.
	Skill Gaps	Shortage of skilled workers in digital technologies and AI.	Invest in training programs and recruitment of specialists.
Operational Challenges	Battery Dependency	Wearables require frequent charging, disrupting routines.	Develop wearables with longer battery life or alternative energy solutions.
	Reliability of Technology	Devices fail under harsh environmental conditions.	Design durable devices that withstand extreme conditions.
	Data Overload	Difficulty managing and analyzing massive data volumes.	Use advanced analytics tools and computational resources.
Regulatory and Compliance Challenges	Evolving Regulations	Unclear and inconsistent standards hinder tech deployment.	Overcompensate for compliance and adapt to changing regulations.
	HSE Compliance	Ensuring devices meet health and safety requirements.	Conduct rigorous testing and validation.
Economic Challenges	High Capital Expenditure	High upfront costs deter adoption, especially for SMEs.	Create financial strategies to manage initial investment costs.
	Uncertain ROI	Long-term ROI uncertainty slows adoption.	Demonstrate benefits through data and successful case studies.
Environmental Challenges	Energy Consumption	Increased power demands conflict with sustainability goals.	Balance digital transformation with energy efficiency initiatives.
	E-Waste Management	Frequent obsolescence leads to increased electronic waste.	Develop strategies for responsible recycling and disposal of devices.

4.3.1. Technical Challenges

Technology is being tested and applied in various ways in the O&G industry, but there remain several technical barriers to wider innovation. One of the main barriers to innovation in O&G is that there are many available technologies that are simply not mature enough to effectively address complex challenges in the industry. In particular, there is a lack of technologies that can deliver sophisticated real-time predictive analytics, autonomous functionalities, and rugged solutions designed to operate over long periods of time in extreme conditions. Currently available technologies are limited by issues of processing power, battery life, and wearability, among others [72,74]. As a result, some innovations that are available in other industries are simply not adaptable to O&G applications.

In addition to these challenges, the adoption of IoT, advanced computing and AI within the O&G sector is further complicated by the need to interface with legacy systems that may require upgrading, retrofitting or replacement [20,21]. This presents a significant decision for the industry in terms of the level of investment required to realize improvements in process optimization and efficiency that can add real value to the bottom line for O&G companies.

While there are many benefits of wearing IIoT-enabled devices and utilizing a range of sensors around plant operations, there are also increased risks to the security and privacy of the vast amounts of data generated and collected. As more data is captured on day-to-day operations and individuals' tasks, there is a growing concern about cyberattacks and industrial espionage, with the potential to place plants and operations at risk. Ensuring the confidentiality, integrity, and availability of this increased volume of data is critical [13,63,64]. As with any IT system, it is essential to have an appropriate cybersecurity strategy in place to mitigate these new risks. However, protecting this type of system is crucial not only from a cybersecurity perspective but also in terms of worker safety and operational reliability.

Remote and offshore locations pose particular challenges in terms of the necessary infrastructure required to support IIoT initiatives and wearables [4,24]. Often, locations may have a communication network, but not a robust enough one to support real-time data transmission or the active use of devices. Supporting such initiatives will require significant investment in new infrastructure, such as towers, power supplies or satellite links, along with complex logistical efforts to deploy and maintain them.

Scaling up to full production is a major problem to overcome for many of these technologies, beyond the small- to medium-size pilot projects that have been run to date [5]. Whilst these projects have demonstrated promising results, in full production, the costs can become prohibitive and the efficiency in terms of production can fall. The O&G industry requires cost-effective and efficient solutions that can be scaled up in a robust manner.

4.3.2. Cultural and Organizational Barriers

While the Oil & Gas industry faces many technical challenges to implement innovations using advanced technology, not as much attention is placed on the cultural or organizational barriers that stop innovation from occurring. One major organizational barrier to successfully embracing innovation is the workforce's resistance to change. Many employees are rooted firmly in the traditional O&G workflows and can be fearful or resistant engaging with new technologies. Employees who have been rooted in a legacy workflow for some time are concerned that technological innovation will lead to job loss, closer monitoring or scrutiny, or a host of other negative implications. This workforce resistance is one of the major barriers to effectively implementing technological solutions [42,65]. This review looks at how to address this particular challenge to successfully change man-

agement and considers how simple communication, wider involvement and basic training can help to build the skills and confidence of the workforce.

In addition to the technical hurdles, the management challenge must not be underestimated. Senior managers need a clear understanding of the benefits of implementing advanced technologies before they will commit resources to prove them in real-world applications. The initial investment required to establish a pilot infrastructure is high and the associated payback period is long-term. But the biggest challenge is to develop and present a clear business case that demonstrates how technology will deliver strategic objectives. Evidence, examples and live demonstrators are crucial to building this understanding [7].

Although there are many benefits of having advanced systems within a business and organization, there are also many challenges, and arguably one of the biggest problems that businesses are facing is the need for a skilled workforce to deliver these implementations. With many businesses striving to develop capability in digital technologies, artificial intelligence and data analytics, there is an absence of in-house skills to address these needs [110]. Filling this skills gap will require businesses to invest significantly in training existing staff and in recruiting new specialist talent. This is a costly and time-consuming process, but ultimately one that is necessary to ensure that businesses have the necessary skills to deliver effective implementations of advanced systems.

4.3.3. Operational Challenges

In addition to the technological challenges that advanced technologies pose to the O&G industry, there are many operational challenges to the daily deployment of these technologies. Many of the wearable technology tools introduced require batteries to operate. For instance, if batteries are not charged properly and on time, those devices will be out of operation and unavailable when perhaps needed most. The wearables of the future need to be designed with longer battery life or alternative energy solutions that can harvest energy on the go [67,74]. Solar power and energy harvesting are two examples of these types of solutions that can keep workers' devices powered throughout the shift.

Reliability of technology in harsh operating environments is a significant challenge within the wearable, HDT and IIoT ecosystem. Many wearables and IIoT devices are deployed in environments characterized by high temperature and pressure, exposure to dust and other environmental hazards, such as aggressive and corrosive chemicals. The impact of these factors on hardware devices can result in significant maintenance and replacement costs. Devices must be developed with rugged, durable and reliable technologies to sustain operational excellence [68,69].

In addition to the technical complexities, there is also an issue of data overload on individuals and organizations. Whilst many of these advanced technologies can generate large amounts of complex data that can be processed automatically, there is also a need for efficient data management systems, powerful analytical capability, large computational power and appropriate skills to interpret the results. Unless efficient data processing methods are in place, the increase in potential will likely be accompanied by little real benefit for many organizations. Efficiently addressing these new challenges will require investment in technologies such as edge computing as well as advanced artificial intelligence-driven analytics capability [93,106].

4.3.4. Regulatory and Compliance Challenges

There is significant pressure in the O&G industry with respect to the regulatory and compliance aspects of digital technology implementation. From a purely regulatory perspective, new rules and regulations emerge frequently, placing a significant burden on stakeholders. From a compliance perspective, while there is a general lack of consistency

and harmony across countries and regions, companies struggle to design and implement digital solutions while maintaining compliance with local, country-specific regulations and standards [2,3]. Technology is evolving at an incredible pace, creating an ever-changing regulatory environment that sometimes exceeds the industry's ability to comply, with companies going above and beyond to meet new rules and regulations.

HSE departments are seen by many as a barrier to the successful adoption of digitalization, wearables and IIoT technologies. Ensuring reliable data collection will be a significant issue given the need for extensive testing and validation. But not complying with these regulations puts workers and the environment at risk and is the very reason for deploying the technologies in the first place. Health, safety, and environmental concerns must be addressed before deploying a new solution in a project since batteries can explode, devices fall apart, wearables get trapped in machinery, and many incidents could happen if the technology deployed does not follow the safety procedures established [72]. In some cases, due to the innovative solutions deployed, HSE does not have the proper knowledge to evaluate risk assessment, which slows down the deployment process until a proper evaluation is done by subject experts.

Besides safety, emerging technologies also require addressing key regulatory and compliance considerations. It is crucial that the industry can validate innovations within the sector against existing and evolving requirements. Other sectors such as finance have created robust ecosystems of stability and compliance through validation of innovative products and services. The future of the O&G sector will rely on the successful integration of digital solutions that enhance safety and are compliant with regulatory requirements. Industry leaders must work alongside all stakeholders to determine guidelines and processes for the adoption of new innovations.

4.4. Future Research Directions

The O&G industry is rapidly transforming by incorporating an extensive range of digital technologies. To steer future developments in deploying Human Digital Twins (HDTs) and O&G-related AI-powered wearables, proactive actions with careful considerations and collaborative approaches by all relevant stakeholders need to be taken to address the operational challenges. In this article, we highlight several important research areas that need to be addressed to make digitalization a reality for improving operational efficiencies and reducing risk in O&G.

4.4.1. Develop Robust Infrastructure for High-Performance AI Systems

Future work will require innovative communications and energy solutions to support the use of emerging technologies within remote and offshore industrial environments. Satellite, LPWAN, renewable energy and portable power technologies (e.g., batteries, energy harvesting, solar-charging) will all have relevance, since future technologies in wearable and IIoT devices will require high computing capabilities to run embedded AI models [24–27]. However, key to the development and integration of these solutions will be collaboration between technology suppliers and relevant industry partners, working together to identify cost-effective and scalable technologies that meet the challenges of these environments.

4.4.2. Enhance Cybersecurity Measures

Future research should focus on the integration of more robust encryption methods, improved intrusion detection and cyber-secure operating practices into the upstream O&G industry [63,106]. Sharing of threat information across industries is critical to aid the O&G industry in its defense against cyberattacks. Blockchain technology could be used for improved data management, providing a secure and transparent environment [13].

4.4.3. Upskill the Workforce

There is a severe lack of skilled labor that can operate and maintain these complex digital systems. In future research, it will be important to consider the need for comprehensive training interventions that support the up-skilling of the current industrial workforce in order to develop the technical skills required to program, operate, maintain and manage the complex digital technologies, AI and data analytics that are increasingly being implemented within these industries. This will require close collaboration with education and training providers to design and evaluate effective training methodologies and approaches. In addition, simulated training environments utilizing VR/AR technologies could play a significant role in the future in providing immersive, real-time training scenarios across a variety of related industries [77,108].

4.4.4. Foster Organizational Change

As future technology becomes more of a determinant of competitive success in the marketplace, cultivating an innovative culture is critical to realizing benefits from future technology. Future research could focus on managing organizational change and how to engage all stakeholders throughout the innovation process. Employees must understand the benefits of new technology, such as job safety and data privacy [42,65]. As employees are more likely to participate in digital initiatives that they find engaging, strategies such as gamification will become increasingly relevant. Gamified approaches—for example, challenging employees to complete complex tasks and providing interactive leaderboards—can increase engagement with initiatives and strive for success. Research around employee engagement, gamification and incentives for these metrics may also provide insight into increasing trust and support for the organization's digital transformation.

4.4.5. Collaborating with Regulators

The increasing complexity of the regulatory environment is preventing organizations from fully leveraging new digital technologies [2]. Future research could explore ways in which organizations can be more proactive in their engagement with regulators to push for clear, consistent and forward-looking guidelines. Collaboration with regulators could help organizations anticipate future compliance issues and develop technologies that are fully compliant from the outset, preventing future problems. Industry-wide frameworks to support future compliance and interoperability could also help organizations to implement new technologies effectively.

4.4.6. Explore Modular and Scalable Solutions

Future research requirements for the deployment of technology should include an assessment of the potential for modularity and scalability to maximize flexibility across different scenarios. Importantly, future research should also consider the requirement for systems to be able to operate in an interoperable manner with currently existing technology to allow seamless integration into ongoing commercial businesses [43].

4.4.7. Address Environmental Sustainability

The environmental impact of digital transformation is a hot research topic. Future research could focus on energy-efficient solutions, energy-efficient devices and systems, efficient recycling of old electronic equipment (e-waste), and the use of renewable energy sources to power Wearables and IIoT devices [116,122]. The industry and research should look into these aspects to be sustainable in the long run and to achieve global sustainability goals.

5. Conclusions

This review, based on 142 studies systematically selected from an initial pool of 850 records following the PRISMA 2020 methodology [28], shows the potential of Human Digital Twins (HDTs) and AI-powered wearables in O&G construction, enabling safety, efficiency and decision support. The use of HDTs, Wearables and Artificial Intelligence within the Industrial Internet of Things (IIoT) environment provides key solutions to improve site safety, construct more efficiently and reduce downtime on remote and offshore hazardous environments. These technologies, deployed and operating in challenging hazardous environments, will unlock innovation and improvements to construction productivity and safety.

Human Digital Twins (HDTs) are beginning to make it possible to plan ahead for safety and for optimal crew planning. Supervisors can monitor the health of their workers and the factors that affect their well-being, and also monitor external and physiological factors that could affect their safety and performance. AI-powered wearables are equipped with various sensors and, combined with AI-powered algorithms and the real-time data they collect, they monitor workers' health, detect potential ergonomic risks, find the best way to complete a task, and prevent accidents and injuries through proactive safety. The integrated solution fosters a culture and work environment focused on safety, wellness, and prevention, supporting efforts to keep workers safe and healthy in difficult working conditions.

Industry-reported figures illustrate both the problem and the opportunity: a National Safety Council survey found that 33% of workers—and 60% of those in construction—believe their employers prioritize productivity over safety [123], while non-peer-reviewed industry reports suggest that digital twin technology can improve project scheduling by 28% with significant cost savings [126]. In line with the evidence tiers described in Section 3.3.3, these figures originate from industry sources rather than peer-reviewed studies and still await independent validation. Across the five HDT application areas and the seven categories of AI-powered smart PPE analyzed, the potential for improving safety and productivity in O&G is therefore significant. However, there are many challenges to its adoption. Data security and high initial investment are major concerns for adoption, along with resistance from workers who do not want to have to operate with emerging technologies. The massive data generated by these technologies must be processed and managed safely and securely. Developing accurate and interoperable digital twins is an emerging area of research and development that requires substantial advancements in both technologies and infrastructures. Achieving interoperability between devices and systems represents a significant technical challenge that requires interdisciplinary innovation across industries.

Future research will be needed to address future challenges for the wider adoption of wearable tech in the O&G Industry. In the short term, some standardization in data security and wearables' cost is needed. Making wearables more accessible to the entire workforce would also be crucial. Well-designed training and education packages for the next generation of field workers could pre-empt a lot of the misconceptions and fears that exist with the current generation of operators. Future research could also investigate the utilization of more advanced Industrial Internet of Things (IIoT) solutions, including Edge Computing.

The intersection of HDTs, AI powered wearables, and IIoT is an emerging field in the O&G sector that has yet to be explored in depth and has many gaps that need to be addressed in order to make this industry much safer, efficient, and sustainable. This intersection of new technologies has the potential to set a new benchmark for the O&G construction industry and other industries moving towards digital technology. By exploring

the challenges and roadblocks of current practices and emerging technologies, industry practitioners and stakeholders will learn how these technologies can improve safety and efficiency while also promoting better worker welfare, increased productivity, and job satisfaction.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AR	Augmented Reality
BLE	Bluetooth Low Energy
CPS	Cyber Physical Systems
DL	Deep Learning
DTs	Digital Twins
EPC	Engineering, Procurement, and Construction
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
HDTs	Human Digital Twins
HR	Heart Rate
HRV	Heart Rate Variability
HSE	Health, Safety, and Environment
IIoT	Industrial Internet of Things
IoT	Internet of Things
ISP	Internet Service Provider
LPWAN	Low-Power Wide-Area Network
ML	Machine Learning
NIOSH	National Institute for Occupational Safety and Health
NLP	Natural Language Processing
NLTK	Natural Language Toolkit
O&G	Oil and Gas
O&M	Operation and Maintenance
PPE	Personal Protective Equipment
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PTW	Permit-to-Work

ROI	Return on Investment
SMEs	Small and Medium-sized Enterprises
UWB	Ultra-Wideband
UV	Ultraviolet
VR	Virtual Reality
WSDs	Wireless Sensor Devices

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