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CONTEXT OBTAINING METHOD IN SUSTAINABLE WORKPLACES

M.I. Yakubovych, V.Y. Lyashkevych

Ivan Franko National University of Lviv
50, Drahomanova str., Lviv, 79005, Ukraine
Emails: maksym.yakubovych@lnu.edu.ua, vasyl.liashkevych@lnu.edu.ua

The modern workplace is rapidly transforming into a complex cyber-physical environment that combines people, technology systems, surroundings, production processes and knowledge. This multidimensionality claims to continuously obtain contextual information, including dynamic information about the status of space, equipment, people and processes, which determines the possibilities for adaptability, security and sustainable management. The paper identifies the role of context as a basic element of adaptive management, reveals the interdisciplinary nature of contextual data, and shows how its correct acquisition affects safety, energy efficiency, productivity and employee well-being. The research methodology includes an analysis of the literature and modern technological solutions, a systematization of context types, the construction of a comparative table of the advantages and disadvantages of existing methods, as well as the use of semantic, expert and simulation validation for a preliminary accelerated assessment. The main results show that each singular method has significant limitations: computer vision (CV) suffers from occlusions, wearable sensors from user unacceptability, digital twins (DTs) from modelling complexity and knowledge graphs (KGs) suffer from high requirements for ontology engineering. The proposed method, based on the hybrid approach, demonstrates the highest accuracy of context obtaining, robustness to data gaps and transparency of solutions based on explained models and semantic integration. The findings show that a combination of physical, semantic and behavioral sources of information provides the most complete picture of the workspace environment states. The proposed context obtaining method integrates heterogeneous data and increases the level of intelligence of workspace management systems. The work contributes to the development of scientific thought in the field of resilience, cyber-physical systems and intelligent monitoring, and also lays the foundation for building adaptive, human-centric decision support systems and automatic microclimate control systems, increasing production incidents and optimizing personnel workload in real workspaces.
Keywords: sustainable workplace, context obtaining, digital twin, knowledge graphs, machine learning, explainable artificial intelligence, computer vision.

Introduction. Today, human productivity has become a multifactorial system, and the modern work environment is determined not only by physiology but also by many other factors. Among such factors, one can list: cognitive load, emotional state, quality of interaction with information systems, nature of tasks performed, etc. It used to be believed that if an employee had warmth, light, and fresh air, they would automatically perform better, but today we know that this is not the case. Even ideal physical comfort does not compensate for excessive information noise, constant notifications, task inconsistency, digital fatigue, etc. It is obvious that physical parameters are no longer the main limiting factor of productivity and, accordingly, the criterion for evaluating the workplace and environment.

Only such a multifactor model can assess why productivity is falling or rising, and what really needs to be changed - intelligent monitoring that analyzes: physical parameters, behavioral patterns, digital patterns, social context, etc. Context in such environments is formed at the intersection of data about people, the environment, equipment, production processes, and regulatory requirements, which determines the critical need for methods for its accurate, timely, and explainable obtaining. Given the rapid digitalization of production, the growing role of IoT, DTs, and intelligent security systems, the formation of a reliable context is becoming the basis for effective and sustainable management.

Literature review. The concept of a sustainable, human-centric workspace is becoming increasingly relevant due to the growing ability of information systems to sense, interpret, and predict context in real time. Recent research on the persistence of cognitive and context-sensitive decision-making systems emphasizes that context is no longer a static attribute of the environment, but a dynamic, multidimensional signal that must be continuously acquired, integrated, and interpreted to maintain persistent intelligent environments [1]. The systemic overview of Industry 4.0 and intelligent product and service systems also highlights contextual awareness as a key capability of the cyber-physical manufacturing and service ecosystem, and emphasizes the need for robust architecture, interoperability, and semantic modeling [2-3].

Broadly speaking, within this broader area, methods for obtaining contextual information in the workplace can be summarized into several main research areas:

- environmental monitoring based on IoT sensors;
- workplace surveillance based on CV;
- wearable devices and methods for measuring human activity;
- cyber-physical modeling based on DTs;
- contextual modeling based on semantics and KGs.

Each approach has its own unique advantages and limitations when applied to sustainable workspaces (SWs) that must simultaneously ensure safety, resilience, productivity and well-being.

Many works treat context primarily as a function of environmental parameters such as temperature, humidity, air quality, occupancy and energy consumption, measured via dense IoT sensor networks. Thus, in [4], was considered energy conservation as one of the components of the smart sustainable management system using Arduino microcontroller. After, in [5], the autoregressive models have demonstrated high accuracy in predicting electricity consumption and monitoring, which allows for prompt response to inefficient use of resources and reduction of electricity costs.

Reviews of many other scientific resources note that IoT-based monitoring systems have been successfully deployed to collect environmental data using temperature, humidity, gas and motion sensors, enabling energy-efficient control of HVAC systems, predictive maintenance and optimization of production processes [6]. In the workplace domain, such systems are often integrated into “smart office” or “smart workplace” solutions that adjust lighting and microclimate to reduce energy use while maintaining basic comfort. However, sensor-only approaches capture mostly physical aspects of context and provide limited insight into cognitive load, work patterns, social interactions or task complexity. The considered types of context its measurement methods were listed in [7].

CV techniques extend context obtaining to visual observation of workers, tools, postures and activities. In industrial and construction settings, CV is widely used to monitor safety, detect unsafe behaviors and analyze human-machine interactions. For example, studies on driver behavior monitoring and intent interpretation have shown that video analytics can detect complex behavioral patterns, including inattention, fatigue, and high-risk maneuvers [8]. However, CV-based methods suffer from overlaps, limited camera angles, privacy concerns, and high computational requirements. In crowded offices or flexible hybrid workspaces, line-of-sight limitations and dynamic layouts further limit the reliability of purely visual context obtaining.

Recent research combines wearable device data with IoT infrastructure for human activity recognition (HAR), inferring behavioral patterns and assessing physical activity [8]. Nevertheless, there are issues with long-term user adoption, intrusiveness of the devices, the need for calibration, and sparse data when workers do not wear the devices continuously are consistently reported in various sources.

In the Ukrainian scientific community, DT technology is being actively researched as a fundamental platform for digital management and monitoring. For example, in [9], industrial DTs describes the twin as a proxy that aggregates sensor data and exposes it via APIs to different business systems, thereby improving understanding of the current state and supporting lifecycle management of industrial assets. A collective monograph on the digital transformation of industrial management emphasizes the role of enterprise-level DTs as a “smart” carrier of digital management that enables integrated decision-making and collaboration [10-11]. Despite these advances, the DTs cannot yet fully replace other context obtaining methods.

KG-based machine learning enables context-aware intrusion detection in industrial systems. Results show that semantic integration can improve anomaly detection capabilities and resilience to data heterogeneity [12]. In the manufacturing sector, recent research combining digital twins with KGs has demonstrated how semantic layers can support flexible queries, advanced analytics, and more interpretable decision support [13]. From an architectural perspective, reviews on context-aware systems emphasize ontologies and semantic middleware as key enablers of interoperability and reusable context models across smart environments [2]. However, creating and maintaining high-quality ontologies for complex workspaces requires significant expert input and effective management. This creates a practical obstacle to the widespread adoption of KG-based approaches in daily workplace management.

Recent surveys explicitly connect context-awareness with sustainability and resilience. They, arguing that cognition and context-aware decision-making systems (CCA-DMS) must integrate multiple context modalities such as physical, behavioral, cognitive and organizational, to support sustainable smart environments [1]. In intelligent product service systems, a context-oriented design framework proposes to combine sensor data, user interaction logs, and semantic models to dynamically customize services and improve user experiences [2, 14-15]. In the Ukrainian context, eco-ergonomic research on the “safe and productive digital workplace” highlights the need to jointly consider ergonomic, ecological and organizational factors such as lighting, noise, microclimate, work–rest regimes, safety culture and digital workload, to support both sustainability and productivity [16].

Meanwhile, industry analyses of workplace sustainability and integrated workplace management systems (IWMS) show that modern platforms are increasingly integrating building management, space utilization, environmental monitoring, and employee comfort metrics into a single dashboard [17]. However, most of these solutions still rely on relatively superficial contextual features and do not fully utilize semantic integration or advanced explanation models. However, the paper [18] considers multidimensional trade-off modeling in sustainable workplace management as not only a methodological necessity, but also a strategic condition for achieving a balance between productivity, resource efficiency, and a high level of social responsibility.

Research objective. From scientific review, current research supports the claim that no single method of context obtaining is sufficient for sustainable workplaces. The biggest gap lies in hybrid, human-centric approaches that integrate heterogeneous physical, semantic and behavioral data streams using DTs and semantic models. Therefore, the creation of an appropriate method for obtaining accessible context in SWs is the main goal of this work.

Research results and their discussion. The results of the comparative analysis of methods taking into account the types of context listed in [7] are shown in Fig. 1. A comparative analysis of context types and obtaining methods clearly demonstrates that no single method can provide complete, accurate, and semantically meaningful context in a smart SW. Each approach only covers a part of the context and has limitations related to the subject area. For example:

- CV exceeds with spatial and behavioral context but fails in microclimate, physiology, machine wear and semantics;
- wearables work well physiologically, but cannot monitor the environment, device, etc.
- DT models physical process state well, but it is not a real sensor and requires data from other sources.
- KG provides semantics and compliance rules, but cannot observe reality, which depends on input from CV, IoT, wearables or DT.

- interpretable anomaly detection (XAI-AD) can reveal anomalies, but cannot interpret their causes or apply physical and semantic constraints.

Table 1.

Comparison of observed methods vs types of context in SWs

Type of Context	CV	Wearables	DT	KG	XAI-AD
Environmental / Physical	Proc: Good at detecting lighting, smoke, occupancy, physical hazards. Cons: Cannot measure CO_2, noise; it is bad in lighting, occlusions.	Proc: Can capture body temperature, limited environmental exposure signals. Cons: Cannot measure microclimate; limited long-term accuracy.	Proc: Models HVAC, energy flows, air quality dynamics. Cons: Requires validated physical models; expensive to maintain.	Proc: Adds semantic rules (comfort, safety thresholds). Cons: Needs accurate sensor integration; cannot observe itself.	Proc: Detects anomalies in temperature/noise/energy patterns. Cons: Needs reliable telemetry; cannot sense SW directly.
Worker Behavior	Proc: Excellent for posture, gestures, unsafe movements, ergonomic risks. Cons: Occlusion; privacy issues.	Proc: Perfect for fatigue, overload, motion patterns (IMU). Cons: Requires user acceptance; battery limitations.	Proc: Can simulate typical movements and ergonomic load. Cons: Not real-time unless paired with CV/wearables.	Proc: Adds semantic interpretation (unsafe gesture). Cons: Depends on correct classification from CV/wearables.	Proc: Flags anomalous behaviors using temporal sequences. Cons: Needs training data; may miss subtle context.
Physiological / Psycho-physiological	Proc: Indirect signs only (face stress, movement). Cons: Cannot measure HRV/EEG/EDA directly.	Proc: Best source for HRV/EEG/EDA, stress, fatigue, cognitive load. Cons: Privacy-sensitive; may be intrusive.	Proc: Can simulate fatigue or stress impact on tasks. Cons: Simulation ≠ actual state; no direct measurements.	Proc: Semantic modeling of stress rules (limits, safety bounds). Cons: Needs physiological input.	Proc: Detects anomalies in physiological patterns. Cons: Needs training from wearable data.
Social-Collaborative	Proc: Detects interactions, contact density, group behavior. Cons: Occlusions; multi-person tracking complexity.	Proc: Can detect proximity via BLE/IMU. Cons: Limited spatial accuracy; no team-level semantics.	Proc: Models team workflows, resource allocation. Cons: Does not observe real social dynamics.	Proc: Captures roles, responsibilities, coordination rules. Cons: Needs real-time data input.	Proc: Detects anomalous team-level patterns (overload). Cons: Requires time-series data from multiple sensors.
Equipment & Machinery	Proc: Identifies visual damage, overheating, missing guards. Cons: Cannot detect vibration.	Proc: Can monitor vibration via wrist-worn devices (indirect). Cons: Not reliable for machine states.	Proc: Best for predictive maintenance; simulates wear, load, cycle times. Cons: Requires detailed machine models.	Proc: Enables semantic rules. Cons: Needs correct telemetry mapping.	Proc: Detects anomalies in SCADA/PLC signals. Cons: Sensitive to telemetry loss.
Process / Production Context	Proc: Recognizes operation stages visually (assembly steps). Cons: Visibility; cannot interpret digital flow.	Proc: Captures worker motion contribution in process. Cons: No understanding of process logic.	Proc: Perfect for full process flow simulation, cycle times. Cons: Needs detailed model with calibration.	Proc: Encodes rules (ISO, SOP), workflow logic. Cons: Requires full ontology.	Proc: Detects process anomalies. Cons: Cannot explain high-level semantics alone.
Safety & Risk	Proc: Detects hazards, unsafe zones, falls, PPE misuse. Cons: May miss invisible risks (gas, CO_2).	Proc: Detects physiological and micro-behavioral risk precursors. Cons: Limited environmental hazard sensing.	Proc: Simulates hazards, emergency scenarios. Cons: Not real hazard detection; only model-based.	Proc: Risk reasoning (cause–effect rules). Cons: Needs integration with sensor systems.	Proc: Excellent for anomaly-based safety alerts. Cons: Requires robust training and thresholds.
Resilience & Resource	Proc: Detects occupancy for HVAC optimization. Cons: Cannot measure energy flows.	Proc: Indirectly detects fatigue for productivity trends. Cons: Not suited for resource data.	Proc: Strong for energy, water, waste, CO_2 modeling. Cons: Accuracy depends on model precision.	Proc: Encodes ESG thresholds, sustainability policies. Cons: Needs rich metadata.	Proc: Detects anomalies in consumption patterns. Cons: Only statistical; lacks semantics.
Semantic / Ontological	Proc: Provides raw visual events. Cons: Cannot apply standards or reasoning.	Proc: Captures bio-signals. Cons: Not semantic.	Proc: Calculates physical state, but not norms. Cons: Does not handle ontologies.	Proc: Applies rules, standards, SHACL, compliance. Cons: Needs ontology engineering.	Proc: Adds explainability to decisions. Cons: No standalone semantics.

Therefore, we chose a hybrid approach that integrates DT, KG and XAI-AD into a single workflow since this is the minimum number of methods to cover all types of context. The method (Fig. 1) intertwines sensing, modelling, reasoning, and explainable intelligence to orchestrate a sustainable workplace. It all starts with a deliberately mixed collection of raw data: CV data, wearable telemetry data, IoT tags, programmable logic controller (PLC) or supervisory control and data acquisition (SCADA) control logs and even analog agents from Webot.

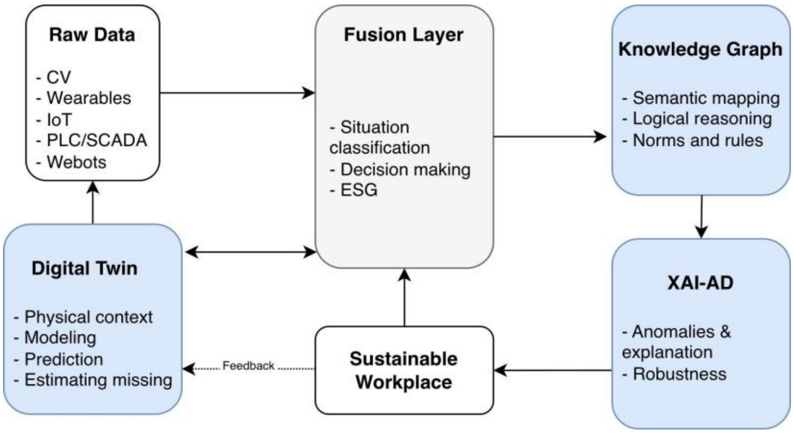


Fig. 1. Context obtaining method in SW

These data streams, which are shown in a PlantUML sequence diagram (Fig. 2), are not treated as independent channels. Instead, they enter a fusion layer that aligns them temporally and semantically, so that a single situation can be identified even if the data patterns differ, such as an operator entering a high-risk area while starting a machine. At this combined level, classification algorithms interpret the operational state, and a decision-making engine weighs responses based on environmental, social and governance objectives, thereby effectively embedding ESG standards into daily operational logic. The integration layer is not isolated. It uses a KG that encodes shared semantics, regulatory rules, and logical relationships between processes, devices, personnel roles, and regulatory obligations.

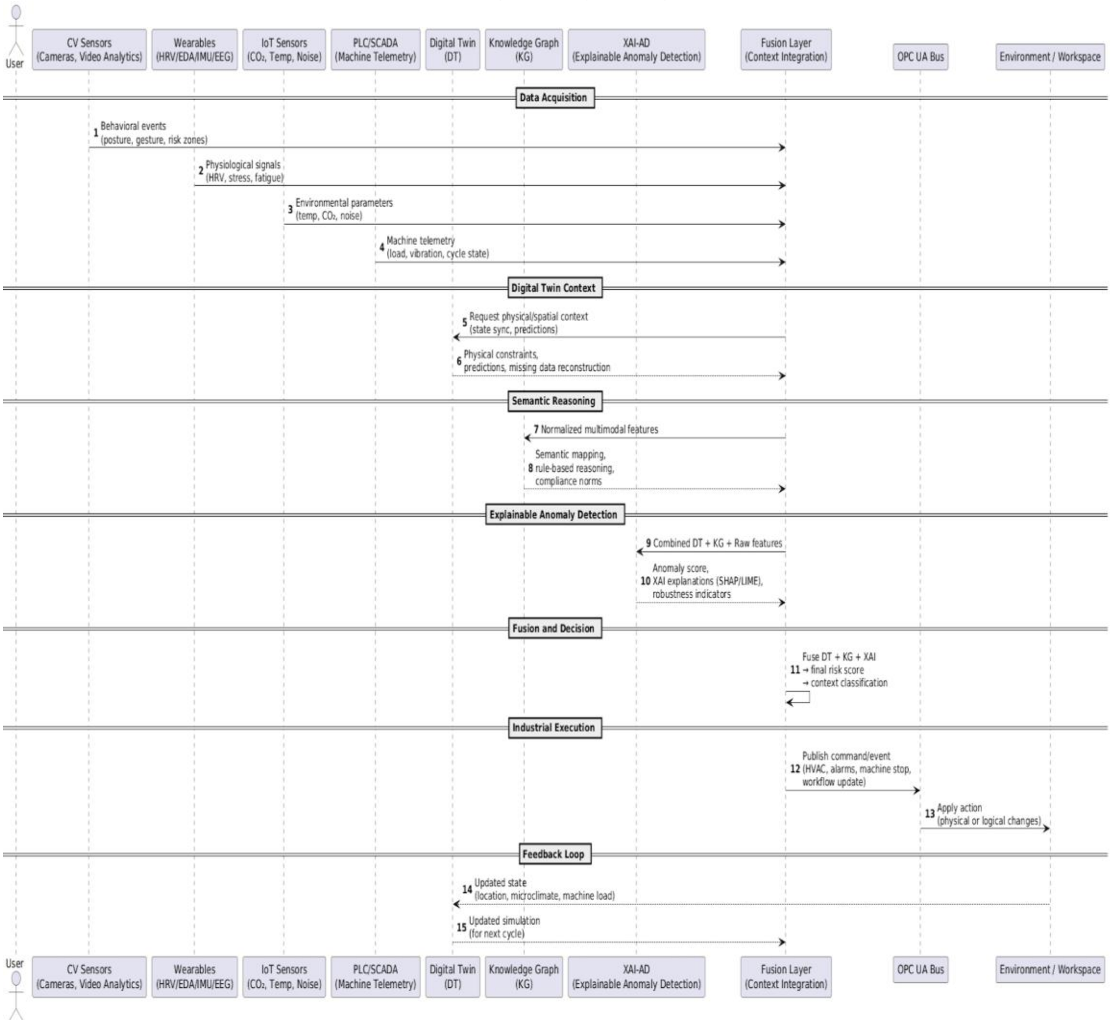


Fig. 2. PlantUML sequence diagram of the proposed method

By projecting the comprehensive observations in a chart, the system gains the ability to infer causal relationships, preconditions and corresponding points. This knowledge system can stabilize the interpretation of events across parts and prevent model deviations when terminology or processes change. This allows for transferring a contextual understanding to the XAI-AD. The XAI-AD component does more than just flag anomalies. It also generates human-readable descriptions, tracks which rules were violated, which sensors contributed most to the alerts, and how confident the system is in detecting violations.

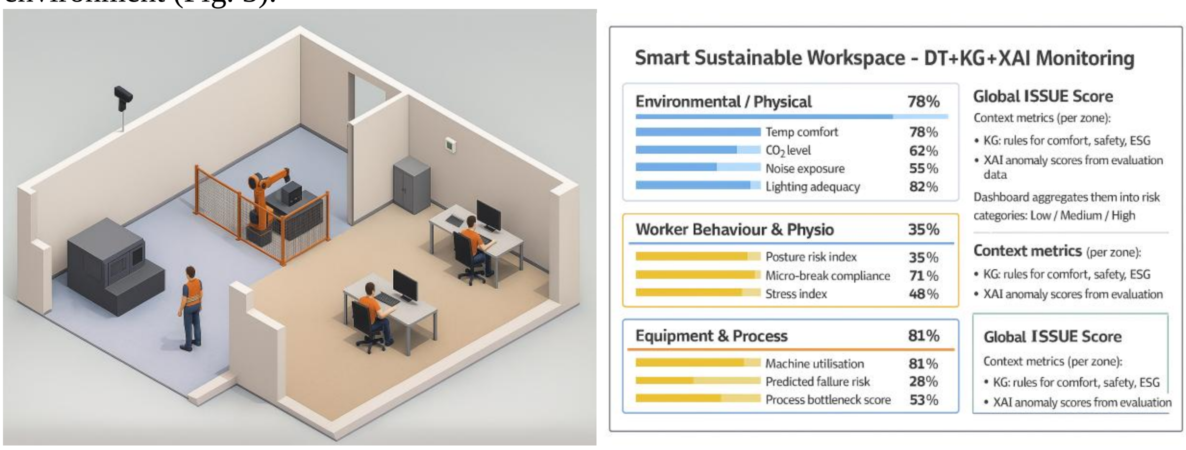
Along with cognitive elements, DTs encapsulate the physical workplace. By receiving the same raw data, they can accurately represent the status of machines, the flow of materials, the movement of personnel and others. When a sensor fails, the DT can fill the gap, predict short-term conditions such as peak energy consumption, and test mitigation strategies without interrupting actual operations. Double-feedback data analysis connects the integration layer and the SW control center, creating a feedback loop that continuously adjusts policies, proactively organizes maintenance, and ensures a balance between productivity, well-being and environmental impact.

The biggest advantage of the proposed method lies in overall transparency because the decisions are made based on a single intelligent system, not isolated dashboards. Prediction and control signals became clearer, resource use aligned with sustainability commitments and interpretable warnings strengthened accountability.

However, integrating all these components (Fig. 2) is no easy task. Coordinating data quality between traditional PLC systems and modern wearable devices is costly, and the knowledge graph requires ongoing management to maintain consistency with the enterprise's classification system. DTs must synchronize almost instantly, which poses challenges for network infrastructure and network security practices. Furthermore, supporting ESG-compliant decision-making standards requires cross-functional coordination. If management shifts priorities or data privacy regulations tighten, the system will adapt quickly or issues being phased out.

Despite the aforementioned challenges, this method provides a solid foundation for continuous improvement. By combining rich contextual information, XAI and virtualization experiments, organizations can gradually create efficient and secure SWs.

To prove the applicability of the proposed method, we did some simulations in the Webots environment (Fig. 3).



a) b)

Fig. 3. Simulations in the Webots environment: a) SW; b) Dashboard with measurements.

For simulation in Webots (Fig. 4a), two key components were created in the environment: DT of the SW with factory and office spaces. Also, two controllers were created: one for data generation and the other for building a dashboard.

The first controller, "context_supervisor.py", simulates the operation of sensors. It reads environmental parameters such as temperature, CO_2, noise, machine load, and worker stress every clock cycle and writes them to CSV. This creates a data stream similar to real IoT systems. There are 10000 generated records which used for the simulation (Fig. 4).

The second controller, "dashboard_controller.py", operates in Supervisor mode, has a “Display device”, which updates the graphical elements in real time. It reads CSV, calculates normalized contextual metrics, generates an integral Global ISSUE Score, defines categories (Low/Medium/High), and draws appropriate blocks on the dashboard (Fig. 4b).

Thus, Webots can simultaneously perform physical room simulation, generate DT data and display analysis results on a dashboard, providing instant and complete simulation of the operation of an intelligent monitoring system.

Discussion of the results obtained. The scientific novelty of the proposed method lies in the creation of a unified hybrid architecture, integrating DT, KG and XAI, which for the first time combines spatiotemporal physical modeling, semantic ontological interpretation and XAI-AD for comprehensive context extraction in SWs.

Unlike existing similar approaches, the method provides multimodal integration of consolidated data, its semantic normalization using KG and reliable deviation detection using XAI models.

It is shown for the first time that the combination of DT and KG allows for compensation for the loss of sensor data, and the addition of XAI provides interpretability, self-explanatoryness and robustness to anomalies.

The method forms a new class of context-oriented systems capable of supporting real-time decision-making taking into account physical, behavioral, psychophysiological, process and normative dependencies.

Conclusions. The paper presents a comparative analysis of modern context obtaining methods from which it follows that no single method can fully capture the diverse and multidimensional context required in smart SWs. The hybrid integration of DTs, KGs and XAI-AD bridges these gaps by combining physical modeling, semantic thinking and robust anomaly detection. This synergy provides high accuracy, interpretability, and robustness to missing or noisy data and a future-ready framework for context-aware decision-making in SW management. The applicability of the proposed method was assessed by using semantic, expert and simulation validation for preliminary accelerated evaluation.

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M.I. Yakubovych, V.Y. Lyashkevych

МЕТОД ВИДОБУВАННЯ КОНТЕКСТУ В СТІЙКИХ РОБОЧИХ ПРИМІЩЕННЯХ

М.І. Якубович, В.Я. Ляшкевич

Львівський національний університет імені Івана Франка
50, Драгоманова вул., Львів, 79005, Україна
Emails: maksym.yakubovych@lnu.edu.ua, vasyl.liashkevych@lnu.edu.ua

Сучасне робоче місце швидко трансформується у складне кіберфізичне середовище, яке поєднує людей, технологічні системи, оточення, виробничі процеси та знання. Ця багатовимірність вимагає безперервне видобування контекстуальної інформації, включаючи динамічну інформацію про стан простору, обладнання, людей та процесів, що визначає можливості адаптивності, безпеки та стійкого управління. У статті визначено роль контексту як базового елемента адаптивного управління, розкрито міждисциплінарний характер контекстуальних даних та показано, як їх правильне врахування впливає на безпеку, енергоефективність, продуктивність та добробут працівників. Методологія дослідження включає аналіз літератури та сучасних технологічних рішень, систематизацію типів контексту, побудову порівняльної таблиці переваг і недоліків існуючих методів, а також використання семантичної, експертної та симуляційної валідації для попередньої прискореної оцінки. Основні результати показують, що подібні методи мають суттєві обмеження: комп'ютерний зір страждає від перекритів, наручні сенсори від неприйнятності для користувача, цифрові двійники від складності моделювання, а графи знань від високих вимог до інженерії знань. Запропонований метод, базується на гібридному підході та демонструє найвищу точність видобування контексту, стійкість до прогалин у даних та прозорість рішень на основі моделей зрозумілого штучного інтелекту та семантичної інтеграції. Результати показують, що поєднання фізичних, семантичних та поведінкових джерел інформації забезпечує найповнішу картину стану робочого середовища. Запропонований метод видобування контексту інтегрує різнорідні дані та підвищує рівень інтелекту систем управління робочим простором. Робота сприяє розвитку наукової думки в галузі стійкості, кіберфізичних систем та інтелектуального моніторингу, а також закладає основу для побудови адаптивної, людиноцентричної системи підтримки рішень та системи автоматичного контролю мікроклімату, збільшення кількості виробничих інцидентів, оптимізації навантаження персоналу в реальних робочих просторах.

Ключові слова: стійкий робочий простір, видобування контексту, цифровий двійник, графи знань, машинне навчання, зрозумілий штучний інтелект, комп’ютерний зір.