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Engineering Intelligent Enterprises: Integrating Artificial Intelligence, Digital Twins and Augmented Reality for Scalable Digital Transformation

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Abstract

Artificial intelligence (AI), digital twins (DTs) and augmented reality (AR) are technologies that are increasingly being adopted by enterprises, and are typically deployed as stand-alone projects. This fragmentation in operation value as AI can make recommendations without a validated representation of the physical system, digital twin can show system behaviours without supporting decisions, and AR can show static information without current analytics. The complementary roles of AI, DT and AR are discussed in this conceptual review and a simplified AI-DT-AR (AIDAR) architecture for scalable digital transformation is proposed. The five layers of the architecture are: Physical and operational system, Data and connectivity, Digital twin, AI and analytics, Augmented interaction. Governance and scalability are considered as cross-cutting requirements, and a closed feedback path is established between operator action and system outcomes, and further model and twin updates. Three couplings are highlighted: twin grounding of AI inputs, evaluating AI recommendations in the twin, and delivering validated decisions to workers via AR. A five-level maturity pathway is also suggested, which moves from disconnected digitization towards governed and composable autonomy. The review indicates that the key enablers for successful integration are semantic interoperability, joint lifecycle management, twin fidelity for decision making and explainable recommendation and human-centred interface design. The framework offers a solid foundation for enterprise transformation, based on a holistic decision cycle instead of simply buying technology.

Keywords: *artificial intelligence; digital twin; augmented reality; intelligent enterprise; digital transformation; Industry 5.0*

1. Introduction

Digital transformation alters the value creation of an organization, the way it coordinates work and the way it makes decisions. It is more than the use of digital tools, it needs adjustment in the strategy, capabilities, processes and organizational structure [1] [2]. Companies that can scan the technological horizon, mobilize resources and reconfigure their operations are more likely to be able to extract long-term value from their investments in digital technologies [3]. In industry, this change is tightly coupled with smart manufacturing, cyber-physical systems and OT/IT convergence [4]. AI, digital twins and AR are playing a significant part in this transition. AI transforms historical and streaming data into predictions, classifications and recommendations [7, 8]. A digital twin is a virtual representation of an asset, process or system that is continuously updated and used for simulation throughout its life cycle [10], [11]. AR can present information in the user's real world and provide instructions at the place where the work is done [12]. Both technologies have proven valuable, however enterprise programmes tend to deploy them separately, resulting in technically powerful components that don't make up a fully functional system. The key point of this paper is that AI, DT and AR are situated in distinct parts of a single decision loop. The twin model represents the actual and potential conditions of the system, AI processes the states and determines appropriate actions, and AR presents the information in a relevant and contextual manner to the worker who can either approve, adapt or take the action. The outcome is new evidence for the twin and analytical models, and alters the physical system. This paper thus presents a staged maturity pathway for implementation, an integrated AIDAR reference architecture and a comparison of the functional

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roles of the three technologies.

2. Conceptual Background

2.1.Digital transformation and intelligent industry

With Industry 4.0 came connected production, horizontal and vertical integration, intelligent automation and data-driven decision making as key design goals. Looking at the reviews on intelligent manufacturing, these objectives rely on the coordinated use of sensing, communication, computation and control and not on a single technology [13]. The empirical evidence also shows that the manufacturing companies are adopting Industry 4.0 technologies in a certain pattern, starting with the connectivity and data infrastructure and proceeding to the more advanced applications of analysis [14]. Industry 5.0 further continues this agenda and focuses on human centricness, resilience and sustainability [15]. This shift is pertinent to AIDAR, as the human interface and the nature of the human-machine collaboration become explicit engineering concerns.

2.2.AI in enterprise operations

AI can be used for anomaly detection, quality inspection, predictive maintenance, scheduling, demand forecasting and resource optimization. Its enterprise value is based on the link between the algorithmic output and the process change. Research on AI driven transformation has shown that the performance improvement is not caused by the model itself, but by the organizational and process capabilities [16]. Data dependency, changing environments, configuration complexity and feedback loops are also sources of engineering debt during deployment [17]. Thus, if the inputs to a high accuracy model no longer reflect the operating system or if the users are unable to comprehend and respond to the model's suggestion, a high accuracy model will still fail.

Explainable AI is a partial solution to this issue, offering evidence regarding influential inputs, model behaviour and uncertainty. However, explanation is more useful when it can be related to a validated system representation. A digital twin can provide that context and can give a controlled environment where the recommendation is tested before it is acted upon. The combination does not remove model risk but it does provide the recommendation with a traceable state, model version and simulation result [18].

2.3.Digital twins

A digital twin is a virtual representation of a physical entity that is connected to it via data exchange. This is because the concept involves system models, lifecycle information and the linkage needed to maintain synchronization of the representation [10]. Industrial research differentiates a digital model with manual exchange, a digital shadow with automated one-way exchange and a digital twin with automated bidirectional exchange [12]. This distinction is significant because whilst a shadow can be used to support monitoring it cannot alone close the operational loop. Digital-twin research has been extended from product design to manufacturing [11] and maintenance and system-level decision support [13]–[17]. Reference models are models describing the integration of physical assets, data, services and virtual models [15]. However, reviews reveal some common challenges such as ambiguities in definition, high cost of modelling, uncertainty of fidelity requirements, lack of interoperability, and incomplete lifecycle maintenance [13, 14]. So, the worth of a twin is not about maximum detail, but about its fidelity being sufficient for the decision it is used to make.

2.4.Augmented reality and human-centred execution

Industrial AR has been applied to assembly, maintenance, inspection, training and remote assistance. Systematic reviews show that when information is correctly recorded, relevant and usable, task time and errors are reduced [19]-[21]. The implementation failures are often due to weak content-management processes, poor integration with enterprise systems, ergonomic limitations and lack of worker involvement [20]. AR should thus be considered as an operational interface, rather than a visualization accessory. Recent research directly relates AR with digital twins to support human-centred industrial transformation [18]. In this model, the twin offers current context on the system, AI offers diagnosis or recommendation, and AR only shows information required for the

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task. Then, operator confirmation, correction and observations can return to the twin. This bi-directional interaction places the worker in the control loop, and enables the human-centred approach of Industry 5.0.

Table 1 Functional comparison of AI, digital twins and augmented reality in an intelligent enterprise

Dimension	Artificial intelligence	Digital twin	Augmented reality
Primary role	Inference, prediction and optimization	Synchronized representation and simulation	Situated communication and human interaction
Main input	Historical and streaming data	Telemetry, models and lifecycle data	Spatial anchors and context-specific content
Time orientation	Predictive and prescriptive	Current-state and counterfactual	Immediate task execution
Main value	Decision quality and analytical scale	Visibility and safe experimentation	Reduced error and improved human performance
Isolated weakness	Limited physical context and actionability	Passive without reasoning or decision logic	Displays content but does not generate insight
Integrated contribution	Selects and explains an action	Grounds and tests the action	Delivers and captures the action at the workplace

3. Research Approach

Literature was examined across digital transformation, industrial AI, digital twins, industrial AR and Industry 5.0. Priority was given to systematic reviews, widely used conceptual studies, reference architectures and papers addressing industrial implementation. The analysis first identified the distinct function, data dependency, time orientation, value contribution and isolated limitation of each technology. These dimensions produced the comparison in Table 1.

The architecture was then derived by matching the limitation of one technology with the capability of another. The need for validated operational context links AI to the twin; the need to assess proposed actions links the model back to twin simulation; and the need to convert analysis into work links AI and the twin to AR. The maturity model was developed by arranging these dependencies in an implementation order. The method supports theoretical synthesis but does not establish empirical superiority, and the proposed architecture should therefore be treated as a testable framework [22].

4. AIDAR Reference Architecture

The AIDAR architecture contains five functional layers and two cross-cutting requirements, as shown in Figure 1. The layers represent responsibilities rather than mandatory products, and one platform may implement several layers. The design follows three principles: separation of concerns, semantic consistency and closed-loop completion. A useful integration should proceed from sensing to interpretation and action, and the effect of the action should become new system evidence. As shown in Figure 1. Five-layer AIDAR architecture with governance, scalability and closed-loop feedback.

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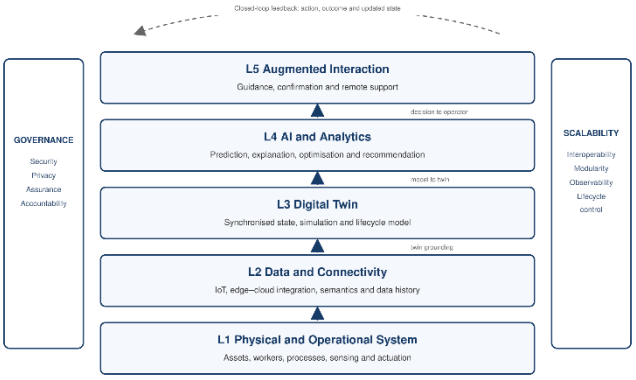

Figure 1 Five-layer AIDAR architecture with governance, scalability and closed-loop feedback

4.1.Physical and operational layer

The first layer consists of assets, infrastructure, workers, operational applications, sensors and actuators. The instrumentation quality and the control authority are the limiting factors at this layer. Key design questions involve what should be monitored, how often it should be monitored and what can be automated. Also, human observations should be acknowledged as operational data, in particular for maintenance and safety conditions which are not fully sensed [11-14].

4.2.data and connectivity layer

The second layer gets, moves, times, stores and harmonizes operational data. Edge processing might be needed for low latency, resilience and data-volume reduction, and cloud services might be needed for broader storage and computation. Semantic interoperability is crucial because if the identifiers, units and meanings are not the same, then the syntactically connected data are not usable. Here, provenance, time synchronisation and quality checks should be defined, in order to be able to audit models and twin states later [15].

4.3.Digital-twin layer

The 3rd layer is asset structure, behaviour, condition and relationships. It provides current state estimation, simulation, what if analysis and lifecycle history. The twin grounds AI by providing a coherent state that is not a set of disjointed values from various sensors. It also creates a more secure setting in which to test an intervention that is proposed. The twin fidelity should be chosen in accordance with the sensitivity and consequence of the target decision, since the detail of the twin will bring the construction and maintenance cost [17.

4.4.AI and analytics layer

The 4th layer includes descriptive, predictive and prescriptive models. It translates twin state and historical evidence into diagnosis, forecast and recommended actions. Uncertainty and adequate explanation should be provided in each output, particularly where there are significant implications for safety, cost/manpower [23]. The version of the model, training data, input definitions and decision thresholds should be documented. Both statistical accuracy and operational benefit should be part of performance monitoring.

4.5.Augmented-interaction layer

The fifth layer provides validated information via AR or other CAI. Spatial and temporal relevance of guidance should be considered, as well as amount of information needed for the task and how to prevent cognitive overload. The operator must have the ability to accept, reject or amend a recommendation and make notes. This feedback is used to update the twin state and is labelled for analytical improvement in the future. AR thus acts as an output and input channel [24].

4.6.The integration couplings and the cross-cutting controls

Whether or not the architecture functions as a system is dependent on three couplings. Twin-to-model grounding allows to connect AI inputs to a validated operational state. Model-to-twin evaluation tests candidate actions under relevant constraints before the actions are implemented. Decision-to-operator situating is the process of converting a validated recommendation to clear guidance at the point of work. The failure of any coupling is a predictable one: analytics that are not grounded, prescriptions or recommendations that are not evaluated and put into action [21]. Governance and scalability span across the layers. Governance encompasses identity, security, privacy, safety, model assurance, human accountability and audit trails. Ethical assessment of algorithms and international guidelines for the

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use of AI highlight transparency, fairness and responsibility as an ongoing need, not a one-off assessment [24]. For scalability, modular interfaces, shared semantics, observability and lifecycle automation is required. Assessment of scaling should be based on the effort needed to add a new asset, process, site or use case.

5. Maturity Pathway for Enterprise Adoption

Before organizations can strive for full autonomy, they need to have reliable data and system representations. Table 2 suggests five levels of maturity. The steps are starting with disconnected digitisation, moving towards instrumentation and synchronised twins, and finally, predictive, prescriptive and human-centred capabilities. Maturity levels vary measurements: early stages focus on coverage and data quality, advanced on decision-to-action time, operational outcomes, resource use and scaling cost. As shown in Table 2. AIDAR maturity pathway and measurement focus.

Table 2 AIDAR maturity pathway and measurement focus

Level	Stage	Integration state	Representative capability	Measurement focus
0	Disconnected	Separate pilots and manual exchange	Retrospective reporting	Data availability and completeness
1	Instrumented	Connected assets and descriptive monitoring	Condition visibility and alerts	Coverage, freshness and latency
2	Twinned and predictive	Synchronized twins supply AI models	Prediction and simulation-supported planning	Forecast error, downtime and false alarms
3	Prescriptive and situated	AI recommendations tested in twins and delivered through AR	Human-confirmed intervention	Decision-to-action time and task error
4	Composable and governed	Federated twins, continuous learning and bounded autonomy	Cross-site optimization with exception oversight	Yield, resource intensity and scaling cost

The maturity model is not intended to be used as a universal score, but rather as a diagnostic tool. Various sites and processes can be at various levels. Progression should be based upon proven consistency at the previous level, such as consistent interfaces, data quality and accountability. This helps to avoid over-ambitious interfaces on a shaky data base, or automated decisions that have not been properly tested.

6. Application Areas

Predictive maintenance is a good illustration of the integration of AIDAR. The twin is updated with sensor data, AI estimates degradation and remaining useful life, twin simulates maintenance

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options and AR guides inspection/repair. Digital-twin maintenance reviews suggest that there is a lot of potential but also that value is dependent on accurate lifecycle data and integration with maintenance workflows [16]. In the same way, industrial case studies show that the twin application can vary from component monitoring to system level optimization [17]. The twin holds the process state, the AI detects anomaly patterns and the AR guides the operator to the corresponding component or inspection point in quality control. The twin provides context and sequence information during the assembly, AI can adjust the next instruction based on the conditions detected, and AR can display the instruction in the worker's field of view. Expert knowledge can be linked to the condition of the actual equipment in training and remote support, instead of being provided as general content. In each of these applications the most important layer may be different, but all layers are essential for a complete loop [18,19].

7. Challenges and Future Research

One of the significant technical challenges is semantic interoperability. Studies of sufficiently expressive domain ontologies and mappings for safe integration with economy to maintain are needed. Another issue is the life cycle management of the joint, since sensors, twin parameters, AI models and AR content have different lifecycles. A separate monitoring of these elements can mask coupled failure; further research could be undertaken to monitor coupled drift and configuration consistency throughout the entire decision chain [16]. More empirical evidence is needed to support the economics of twin fidelity. The fidelity-uncertainty-computation-operational value connection is not necessarily linear and more fidelity does not necessarily lead to better decisions. Research should determine the minimum fidelity for defined risk classes that is relevant to the decision. The same applies to the expenses for maintaining AR content and spatial anchors, when equipment and processes change [17]. Human factors are of paramount importance. Operators might take too much trust in seemingly accurate suggestions, or disregard systems that give insufficient explanations and too many alerts. Future research should investigate the impact of explanation, uncertainty display, workload and professional expertise on trust calibration. Industry 5.0 further emphasizes that the capability, wellbeing and agency of workers should be considered design goals [5, 25]. Longitudinal studies should also assess the effectiveness of integrated systems in enhancing skill and safety, and whether they might over time lead to a decrease in human understanding because of over-automation. The last challenge is governed autonomy. Advanced AIDAR systems can automatically choose, test and execute interventions with minimal human intervention. Each action in an audit record should be associated with the physical state, twin version, model version, explanation and approval pathway. Assurance cases, override mechanisms and responsibility when decisions are made from multiple interacting models and human inputs require research [21].

8. Practical Implications

Transformation programmes should be based on operational decisions, not technology categories. A proposed use case should include the state of the system that is required, the decision to be improved, the person or controller that can make the decision, and the feedback that can be used to measure the result. Investment then should be directed to fill in the missing pieces in that chain. If the recommendation of a technically impressive pilot is outside normal work, or if the result of the pilot cannot be related to the model and twin state [22] the pilot should not be considered successful. Implementation should start with a small, but useful process, include common identifiers and common semantics, and include measuring baseline performance before automation. Reusable interfaces for telemetry, twin services, model serving, explanation/AR content should be defined by the architecture teams. Operations people need to be involved in design and validation from the start. Governance roles, decision limits and incident procedures should be agreed prior to introduction of prescriptive capability [24].

Conclusion

AI, digital twins and augmented reality should be

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designed as an integral component of a closed enterprise decision loop. AI offers reasoning and optimization, the digital twin offers a synchronized and testable representation of the operational system, and AR makes a link between the validated decisions and human action. The proposed five-layer AIDAR architecture includes these functions with twin grounding, model-to-twin evaluation and decision-to-operator situating, and governance and scalability are applied across the entire stack. The maturity pathway that accompanies it helps guide pilots through each stage of the adoption process, from disconnected to governed autonomy. According to the framework, the key to scalable digital transformation is not so much about getting hold of cutting-edge technologies, but about creating robust interfaces between data, models, system representations and people. The next research priority is empirical validation of the architecture and the maturity indicators and decision-relevant fidelity.

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