Smart Digital Twin for Technical Safety Assessment and Asset Integrity Assurance: Categorizing Degree of Autonomation for Reducing Human Cognitive Fatigue

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Abstract. The rapid advancement of industry 4.0 technologies has catalyzed the integration of smart digital twins into technical safety assessment and asset integrity assurance processes. These intelligent systems, powered by machine learning, IoT, and real-time analytics, offer unparalleled potential to enhance decision-making and reduce human cognitive fatigue. This paper presents a framework for categorizing the degree of autonomation in smart digital twins, focusing on their role in mitigating human error and optimizing technical and operational safety. We define autonomation as the interplay between automation and human oversight, and we classify its levels based on task complexity, decision-making capabilities, and human intervention requirements. Case studies in industrial sectors, such as oil and gas, demonstrate the efficacy of the proposed framework. The findings highlight that appropriately calibrated levels of automation enhance the accuracy of safety assessments and promote performance target traceability and sustainable asset management by minimizing operator workload and improving cognitive resilience. This research provides a pathway for implementing smart digital twins to achieve safer, more efficient, and resilient industrial systems.

Keywords: smart digital twin, technical safety and risk assessment, industry 4.0, human cognitive fatigue

1 Introduction

Industry 4.0 has introduced transformative technologies such as the Internet of Things (IoT), artificial intelligence (AI), and advanced data analytics, driving innovation across industrial sectors [1, 2]. Among these advancements, Smart Digital Twin (SDT) have emerged as pivotal tools for technical safety assessment and asset integrity assurance [3]. By creating real-time, data-driven virtual replicas of physical systems, SDT enables predictive maintenance, risk mitigation, and process optimization with unprecedented precision [4, 5]. These capabilities are particularly critical in industries such as oil and gas, where safety and reliability are paramount.

The oil and gas industry operates in a complex, high-risk environment where technical safety and asset integrity are critical to both operational efficiency and workforce safety [6]. Equipment failures, unplanned downtime, and safety incidents can lead to severe consequences, including environmental harm, significant financial losses, and even loss of life [7]. While effective, traditional asset management and safety assurance practices often involve considerable human oversight; operators must process large volumes of complex data and make rapid, high-stakes decisions [8, 9]. This manual approach heightens the risk of human error and contributes to cognitive fatigue, especially in roles that demand constant vigilance and quick response to dynamic conditions.

Digital twin digitally represents physical assets, systems, or processes, mirroring their real-time status through continuous data integration [10]. These virtual models enable operators and engineers to monitor asset health, predict failures, and identify potential safety risks before they escalate, facilitating a proactive approach to asset management [11, 12]. By offering real-time insights and automating routine monitoring and analysis tasks, digital twins significantly reduce the cognitive load on human operators, allowing them to focus on critical decision-making with enhanced clarity.

Despite their potential, implementing SDT involves addressing key challenges, particularly balancing automation with human oversight [13]. The concept of "autonomation," which describes the interplay between automated systems and human control, plays a crucial role in this context [14]. While higher degrees of automation can reduce human error and enhance efficiency, they may also lead to cognitive fatigue when operators are required to manage complex, high-stakes decisions without sufficient support [13]. Conversely, under-automation can burden human operators with repetitive tasks, increasing the likelihood of errors and inefficiencies.

This paper proposes a framework for categorizing the degree of autonomation in SDT tailored to reduce human cognitive fatigue while optimizing technical safety and asset integrity. By systematically classifying automation levels based on task complexity, decision-making capabilities, and human intervention requirements, the framework addresses the dual objectives of enhancing operational safety and sustaining human cognitive resilience. Through the classification and categorization of DT autonomation, stakeholders in the oil and gas industry can assess their current capabilities and roadmap for advancing the autonomy of their digital twins in creating safer, more efficient, and resilient industrial operations.

2 Background and Literature Review

2.1 Smart Digital Twin (SDT)

SDTs are virtual representations of physical systems that mirror their behavior in real-time or near real-time [15]. With the advent of the Internet of Things (IoT), machine learning, and cloud computing, digital twins have been extensively used across manufacturing, healthcare, and infrastructure management [16]. SDTs incorporate uncertainties into these models, enabling risk assessment and safety analysis. Despite the level of research achieved so far, these integrated models have yet to achieve the level of implementation described in the research.

The concept of SDT for risk assessment has gained significant attention in various industries. [17] focused on probabilistic methods for risk assessment of airframe digital twin structures, highlighting the importance of incorporating uncertainty in the assessment process. [18] extended this concept to transmission pipelines, emphasizing the need for SDT to assess risks effectively. [8] discussed the development of a digital twin reference model to prevent operators' risks in process plants. This work proposed a reference model for digital twins in process plants to enhance risk control and prevention, emphasizing the potential benefits for operator safety, cost reduction, and overall business improvement in the context of offshore oil and gas platforms. Similarly, [19] proposed a quantitative risk assessment method for cyber-physical systems using probabilistic and deterministic techniques to identify critical assets that require cybersecurity measures. The advancement in the use of automated DT for risk assessment poses a new cybersecurity threat to prevent malicious intrusions into the model.

Grimmeisen [20] introduced a method for generating hybrid probabilistic risk models from SysML v2 models of software-defined manufacturing systems. This approach aimed to automate the generation of reliability models from digital twin formalism, enhancing the efficiency of risk assessment processes. [21] proposed a public opinion digital twin for public opinion analysis, demonstrating the versatility of digital twin concepts in various domains. Furthermore, Liao [22] presented the Airframe Digital Twin (ADT) framework for aircraft structural life-cycle management, focusing on reducing maintenance costs and extending the useful life of aircraft components. [23] discussed the SCO-FloodDAM-DT project, which aimed to develop a digital twin for flood detection, prediction, and risk assessments on a global scale, highlighting the importance of digital twins in environmental monitoring and disaster management. The application of SDT to different industries and equipment manufacturers could enhance its integration in different applications.

[24] highlighted the importance of transitioning to a digital work environment to improve data analytics and enhance risk assessment and management practices. [25] discussed how digital twins can enhance operational integrity management by accurately estimating maintenance scopes and repairs, ultimately improving asset performance and reliability. [26] proposed a digital twin approach for CO2 pipeline integrity management, showcasing the potential of data-driven models to improve structural integrity and address integrity issues in pipeline transportation. In the oil and gas sector, original equipment manufacturers could have a DT of their products, which can be monitored and managed individually or as a part of an integrated system on offshore platforms.

The literature review indicates a growing interest in smart digital twins for risk assessment across different industries. It emphasizes the need for advanced modeling techniques to enhance safety, efficiency, and decision-making processes. These studies demonstrate the potential of categorizing digital twins to improve risk assessment practices and address complex challenges in various domains.

2.2 Smart Digital Twin for Risk and Safety Assessment

A smart digital twin extends the traditional digital twin concept by integrating stochastic models to account for system dynamics, external influences, and measurement noise uncertainties [17]. This capability is vital for safety-critical systems in sectors like the aerospace, healthcare, nuclear power plants, and autonomous vehicles.

SDTs are emerging as powerful tools for integrating risk and safety assessment in smart industrial environments [9]. They can autonomously identify potential risks, map dependencies, and generate analyses for mitigation strategies [27]. SDTs enable real-time monitoring of human behaviors in smart factories using wearable sensors and computer vision, facilitating automatic risk prediction and avoidance [28]. A Digital Risk Twin (DRT) concept has been proposed to digitize the RAMS process across the product lifecycle, offering integration, visualization, and simulation capabilities [27]. However, challenges remain in addressing the safety, cybersecurity, and reliability aspects of DTs [9]. A reference model for implementing DTs in risk prediction and prevention has been developed, consisting of four layers and five implementation phases [8]. These advancements in DT improved operator safety, reduced maintenance costs, and enhanced overall business in process industries. **Fig. 1** shows the stages for achieving an SDT from a conventional digital twin model.

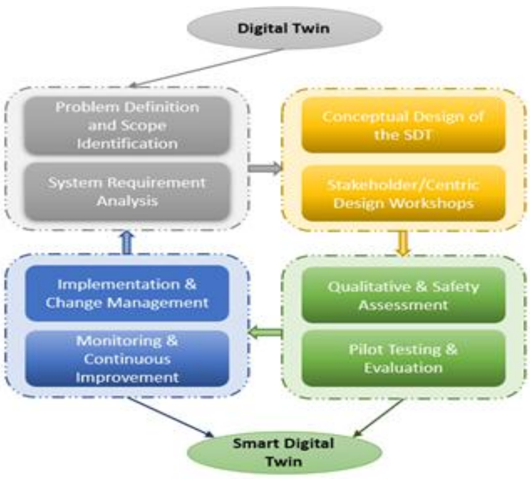

Fig. 1. SDT for risk and safety assessment

2.3 Classification of Digital Twin

For progress tracking, a comprehensive analysis of the various roles digital twins can assume and the degree to which these roles can be automated in collaboration with humans needs to be defined [13]. However, since role allocation is closely tied to classifying different technological capabilities within DTs, we present a summary of existing approaches and frameworks in this area. [13] identifies five levels of digital twins (DTs): (1) Descriptive Twin, a visual representation of the asset; (2) Informative Twin, which collects and consolidates specified data; (3) Predictive Twin, leveraging operational data to forecast future outcomes; (4) Comprehensive Twin, capable of simulating "what-if" scenarios; and (5) Autonomous Twin, which operates independently on behalf of users. [29] offer a classification of digital twins (DTs) based on their levels of automation: Pre-Digital Twin, Digital Twin, Adaptive Digital Twin, and Intelligent Digital Twin. However, this framework does not account for DTs' roles. [30] categorize digital twins (DTs) into three types based on their level of data integration: (1) Digital Model, a digital representation of a physical object with no data exchange; (2) Digital Shadow, which allows one-way data flow from the physical object to the digital counterpart; and (3) Digital Twin, characterized by bidirectional data exchange. This classification focuses solely on data integration capabilities and does not address the various roles DTs can perform or their levels of automation.

To fully leverage the potential of digital twins (DTs), autonomation, and human operators, it is essential to understand the roles a DT can assume and the extent to which these roles can be automated. This study introduces the categorization of the DT framework in the oil and gas sector, combining the percentages of various roles a DT can perform with the corresponding levels of automation for each role.

3 Research Methodology

3.1 Problem identification and validation of SDT development

Implementing SDT for risk and safety assessment with decision-making in the offshore oil and gas industry involves a structured qualitative methodology to ensure effective design, deployment, and adoption. The methodology used in this study focuses on stakeholder engagement, process analysis, and iterative development to align the SDT implementation with the industry's unique needs. Action research within case study-based research is a hands-on, iterative approach where researchers work closely with participants to identify problems, implement solutions, and reflect on the outcomes — all within a specific, real-life case context. The goal is not just to understand a situation but to actively improve it through planning, action, observation, and reflection cycles [31]. **Fig. 2** shows the action research approach used:

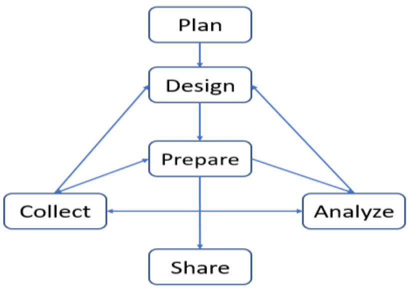

Fig. 2. Illustration of case study research process based on [31]

Using SDT for safety assessment involves creating a virtual model of a physical asset or system and leveraging real-time data, simulations, and predictive analytics to evaluate, monitor, and enhance its safety. This approach enables dynamic, continuous assessment of operational and environmental risks, helping organizations prevent accidents, optimize safety protocols, and ensure compliance with regulatory standards.

3.2 Framework for design and implementation of Smart Digital Twin (SDT)

The offshore oil and gas industry faces unique challenges in ensuring operational efficiency, safety, and risk mitigation. Adopting SDT technology provides an innovative framework for addressing these challenges. SDT integrates real-time data from physical assets with virtual models, enabling continuous monitoring, predictive analytics, and decision-making support [16]. [32] discussed the application of artificial intelligence and automation in pipeline engineering to reduce engineering time and optimize design, particularly in the face of crude price uncertainty.

The framework for designing and implementing an SDT for risk and safety assessment includes the procedures and components shown in **Fig. 3**.

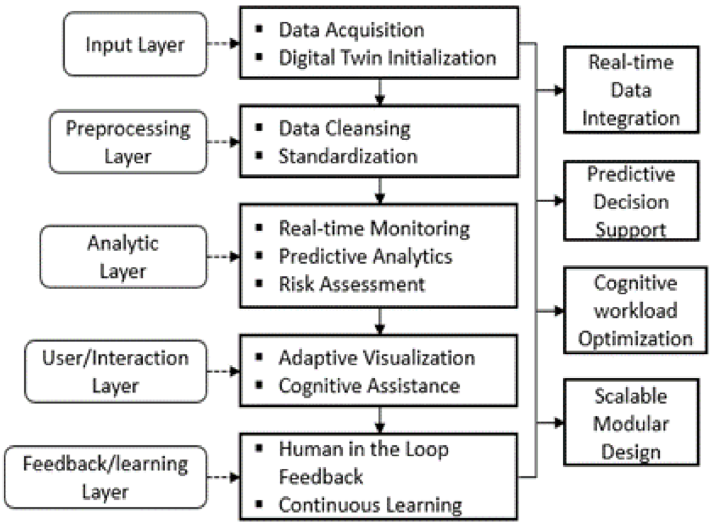

Fig. 3. Framework for the use of SDT for risk and safety assessment

In the Input/data collection layer, real asset sensors, similar asset data, and environmental data are sources for data collection through data acquisition and digital twin initialization. Data preprocessing (e.g., cleaning and standardization) is implemented in the preprocessing layer for a quality digital representation.

3.3 Classifying Levels of Automation in Digital Twins (DTs) for Offshore Oil and Gas Platforms

Research Objectives

The primary objective is to develop a framework to classify levels of automation in Digital Twins (DTs) within offshore oil and gas (O&G) platforms by assessing the degree of integration and autonomy of SDT systems across their lifecycles. The impact of human roles on the operation of DT through a multi-dimensional classification framework for stakeholders is to be established to evaluate and enhance automation capabilities. To ensure comprehensive classification, a two-step, bottom-up research methodology is implemented.

Step 1: Identification of Digital Twin (DT) Functions

Through the literature review, we extensively reviewed academic articles, industry reports, and case studies focused on Digital Twins in the O&G sector. Core functionalities of DTs were identified, particularly in energy management and automation. We also used the expert consultation approach, which involves engaging with subject matter experts (SMEs) from academia, industry, and technology providers to validate and refine the list of DT functions.

Based on the foregoing, a consolidated list of distinct DT functions, categorized based on their relevance to lifecycle stages (e.g., design, operation, maintenance), was established as an outcome.

Step 2: Categorization of Human Roles in DT Systems

The functions and potentials of DT relative to human roles are categorized into Higher-Level Categories through the following approach: (1) Classifying the identified functions into broader categories (e.g., monitoring, control, prediction, optimization) using established frameworks from the literature and expert inputs. (2) Assessment of Human Impact: Analyzing the interaction between human operators and DT systems to determine the levels of human intervention (manual, semi-automated, fully automated) and assessing the impact of human roles on decision-making and system autonomy.

Step 3: Validation of Framework

The developed framework is applied to a case study of real-world offshore oil and gas projects to test its robustness and practical applicability. A feedback loop assessment is implemented to collect feedback from industry stakeholders to refine the framework iteratively. The findings are incorporated into the classification to ensure alignment with industry practices and technological advancements.

Step 4: Classification Scheme

A classification scheme is developed with levels of automation ranging from manual processes to fully autonomous DT systems. Key dimensions include integration (degree of data and system interconnectivity), autonomy (levels of automated decision-making), and lifecycle coverage (stages of the DT lifecycle where the system is applied, e.g., development, real-time operations, decommissioning).

Step 5: Expected Contributions
Establish a roadmap for stakeholders to identify gaps and strategize DT autonomy and functionality advancements. Also, a standardized methodology for classifying DT automation in the O&G sector is established. This will enhance the understanding of the interplay between human roles and DT system performance.

4 Implementation, Analysis, and Results

Digital twin models incorporate deterministic and probabilistic approaches to simulate system performance and assess risks. Deterministic models, such as performance and behavioral models, simulate normal operating conditions and represent system interactions. Probabilistic models, including failure and degradation models, logic and relational models, and surrogate models, predict failure likelihood and dependencies and provide computationally efficient approximations. Integrating these models involves continuous validation and real-time data updates, ensuring robust and dynamic risk assessments. Risk assessment modules leverage probabilistic outputs to identify, quantify, and prioritize risks, enabling scenario evaluations and actionable insights for operations and maintenance.

Interactive dashboards and visualization tools provide clear insights, enabling end-users to explore scenarios, evaluate decisions, and optimize performance, reliability, and safety. This framework facilitates proactive risk mitigation by identifying and addressing potential issues before they escalate, improving safety for workers, equipment, and the environment.

4.1 Safety Assessment Decision-Making Integration to Digital Twin

Human cognitive fatigue, often caused by information overload, repetitive tasks, or high-pressure decision-making, is a significant challenge in industries that rely on real-time data analysis, complex systems, and critical decision-making. Existing methods have not developed an approach for integrating decision-making models in digital twins, requiring human interaction. Bayesian network-based inference models provide a framework for integrating prior knowledge and real-time data for predictive modeling. Additionally, machine learning methods and Monte Carlo simulations can be used for risk assessment, enabling scenario-based analysis under various uncertainty conditions [17].

The comprehensive and robust SDT specified in this paper helps to reduce human cognitive fatigue in the following ways: 1) Real-time and routine monitoring to process data and provide information on critical trends and data points to operators in a visually friendly way, 2) Predict potential failures or inefficiencies, providing decision support for preventive actions, 3) Contextual information delivery using locationaware and task-specific insights, 4) Training and skill augmentation by simulating real-world scenarios for training, enhancing operator skills without exposing them to real-world risks. **Fig. 4** shows the stages in building and integrating safety and decision-making models in SDT.

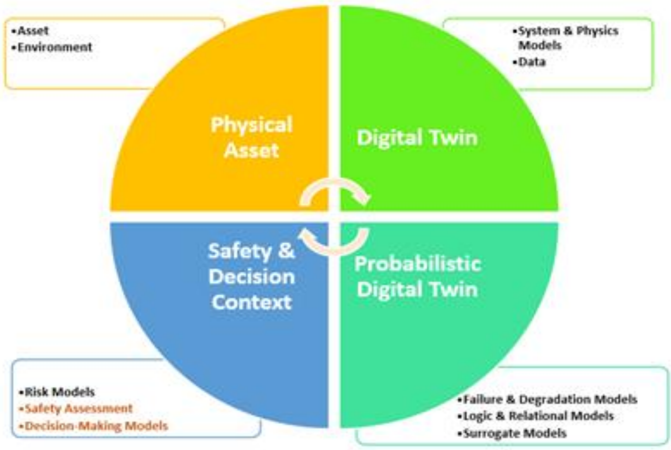

Fig. 4. Integrating safety assessment and decision-making model into digital twin

4.2 Digital Twin Categorization Framework

Classifying levels of automation in digital twins (DTs) for offshore oil and gas platforms requires assessing how integrated and autonomous the DT systems are across their lifecycles. There are a variety of approaches to methodologies, which can be attributed to several factors. One such factor is the growing interest in exploring and implementing Digital Twins (DTs) within the oil and gas (O&G) sector. This may lead to a lack of standardized reference methods and implementation classification levels.

We took a two-step bottom-up approach to identify the impact of humans on DTs. First, we identified obvious DT functions. Then, we identified the roles by grouping those functions into higher-level categories based on literature and expert reviews. A multi-dimensional framework for classifying digital twins has been developed in energy management, including automation levels for search functionalities [33]. This classification system can be applied to digital twins in the oil and gas industry, as seen in the case study on offshore oil and gas drilling occupations [34]. Furthermore, many articles from O&G industry conferences emphasize presenting the final solution and its outcomes rather than delving into the methodological steps involved in designing the DT solution. **Table 1** shows the percentage-based classification with examples for each level.

Table 1. Description for the basis of level classification

S/N	LEVELS	DESCRIPTION	APPLICATIONS	EXAMPLES
1.	Manual Assistance 0 – 20%	The digital twin is primarily a visualization and data repository. Significant human intervention is required to interpret data and make decisions.	Used during the early adoption phase of digital twins for visualization.	3D visualization of the platform's structure for inspection planning.
				Data aggregation from various sources (e.g., sensors, historical logs) without real-time insights.
				Human-led failure diagnostics based on static models.
2.	Assisted Decision-Making 21 – 40%	The DT provides recommendations but relies on operators to validate and implement decisions.	Common in condition monitoring and early predictive maintenance systems.	Condition monitoring using historical trends with basic alarms for anomalies.
				Recommendations for maintenance schedules based on equipment usage patterns.
				Simulations of "what-if" scenarios to predict outcomes of changes in platform operations.
3.	Semi-Autonomous Operation 41 – 60%	The DT supports real-time decision-making and partially automates certain processes.	Utilized in advanced maintenance and safety systems.	Real-time monitoring with predictive analytics for equipment failure.
				Semi-automated control of valves and pumps based on predefined rules.
				Feedback loops where the DT refines simulations and predictions with live data.
4.	High Autonomy 61 – 80%	The DT performs decision-making autonomously for well-defined tasks but requires human oversight for complex or high-stakes decisions.	Emerging in complex optimization and real-time control.	Autonomous scheduling of inspections and repairs based on predictive maintenance algorithms.
				Adaptive production optimization in response to reservoir dynamics or environmental conditions.
				Automated safety interventions, such as system shutdowns during hazardous events.
5.	Full Autonomy 81 – 100%	The DT operates independently, managing and optimizing the platform without human intervention.	A future state for offshore platforms requiring robust AI, IoT, and regulatory alignment.	End-to-end optimization of production and safety systems, including drilling, extraction, and resource management.
				Real-time self-healing systems for equipment and infrastructure.
				Autonomous response to external variables (e.g., weather changes or market demand fluctuations).

This classification can help stakeholders in the oil and gas industry assess their current capabilities and roadmap for advancing the autonomy of their digital twins.

4.3 Case Study Results

In the first step of identifying DT functions, a literature review of 50+ articles, including reports on DTs in O&G, was carried out, emphasizing functions like real-time monitoring, predictive maintenance, and process optimization. Interviews were conducted with 10 industry experts and professionals, including engineers, data scientists, and operations managers in the O&G sector, where the different stages in SDT implementation were defined as: 1) design phase, 2) execution phase, 3) operation and maintenance (O&M), 4) decision management phase.

The second step is the categorization of human function grouping based on **Table 1** and expert feedback. The following were defined for the allocation of weights for each group: 1) Monitoring - Real-time data acquisition and visualization, 2) Control - Incident response and manual adjustments, 3) Prediction - Predictive analytics and risk assessment, 4) Optimization - Energy and production efficiency improvements.

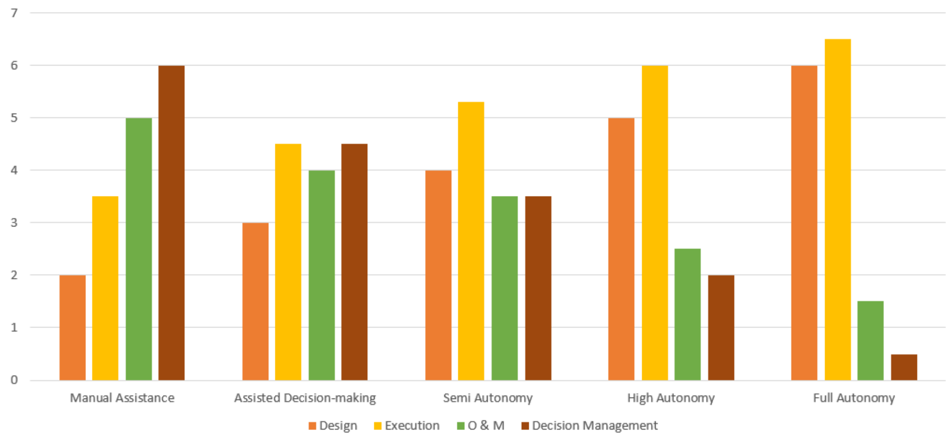

Fig. 5. Human Involvement Levels in SDT Phases.

The key observation is that the level of human involvement at different project stages varies. Higher autonomy reduces human involvement in decision-making however, it requires a lot of resources at its design and execution phase.

To demonstrate a DT implementation and performance of a separation knockout drum on an offshore platform on the Norwegian Continental Shelf, 2 parameters were used: 1) Integration - Connectivity between DTs, physical systems, and external data sources 2) Autonomy: Extent of automated decision-making. The DT system monitors the performance of a separation knockout drum, and the analysis shows that the current DT capability is Semi-automated (Level 2) using the methodology described in chapter 3.

The framework validation compared the classification framework with similar use cases in the O&G industry. The feedback from industry experts validated the practicality of levels and dimensions. The outcome identified gaps in current DT implementations and provided actionable insights to advance DT autonomy from Level 2 to Level 3 or higher.

Table 2. Case study result validation for the level of DT

Dimension	Current Level	Target Level	Key Actions
Integration	Medium	High	Enhance connectivity with external systems.
Autonomy	Level 2	Level 3	Implement real-time decision-making.

By applying this framework, the industry can systematically identify current capabilities and devise roadmaps to achieve greater automation and integration in DT systems.

5 Conclusion

While developing autonomous and SDTs presents significant challenges, the reality is that most current and near-future DT systems will continue to depend on collaboration between humans and computers. This makes it crucial to evaluate how DTs can complement and work alongside humans. However, as DT technology remains in its early stages of development, the oil and gas industry is still yet to harness its full potential and define what levels they are in DT integration. The consequence of this gap is resource misallocation, cost explosion, unrealistic targets, and strategic misalignment.

This work has further defined another step in SDT by presenting a framework for incorporating automated safety decision-making based on real-time transformative advancement in digital twin technology, offering unparalleled safety and risk assessment capabilities. Additionally, the SDT categorization framework has been proposed. The framework is based on the level of human interaction with the DT model thus: a) manual assistance (0 – 20 %), b) Assisted Decision-Making (21 – 40 %), c) Semi-Autonomous Operation (41 – 60 %), d) High Autonomy (61 – 80 %), e) Full Autonomy (81 – 100 %). Without a framework, planning digital twin (DT) deployments becomes more of a subjective exercise than a systematic process, as individuals offer unstructured suggestions regarding the roles DTs should fulfill and the extent of their automation [35].

A case study has been used to demonstrate its application and benefits in the oil and gas industry. The summary of key findings on the framework for reducing human cognitive fatigue and enhancing safety and operational effectiveness is reflected as a catalyst for safer, more efficient industrial environments. The categorization framework plays a pivotal role in this process—not as a prescriptive tool dictating specific levels of DT implementation but as a flexible guide. It facilitates meaningful discussions, comparisons, and communication among stakeholders, enabling them to evaluate and prioritize digital opportunities. By using the framework, organizations can navigate the complexities of digital transformation with a more informed and focused approach.

5.1 Challenges and limitations

Implementing SDT technologies faces several challenges, including data integration issues, cybersecurity risks, and high costs. Organizational resistance, driven by workforce adaptation and change management challenges, further complicates adoption. Predictive accuracy limitations necessitate continuous model improvement. Specific to SDTs, barriers include computational complexity for real-time simulations, difficulties in integrating heterogeneous data, challenges in quantifying and propagating uncertainties, and scalability concerns when applying models to large systems without compromising accuracy. These obstacles require innovative solutions to ensure effective deployment and utilization.

5.2 Future Research Directions

Areas for further study include refining predictive models, understanding human-digital twin interaction, and improving cognitive support tools for practical implementation to enhance safety assessment decision-making. Integrating emerging technologies, like AI and IoT, to enhance digital twin capabilities requires reliability, robustness, and resilience due to safety and environmental implications for humans. Edge computing enables real-time processing of digital twin data at the source, adaptive learning models that continuously learn and adapt to new data and conditions, enhancement of data security and integrity in digital twin systems, and development of regulatory frameworks and guidelines for the adoption of SDTs in safety-critical domains are areas that require improvement.

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