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Managing Data Interoperability Risks in Digital Twin-Enabled Battery Management System (BMS) Projects in Smart Manufacturing Industry

A Project Risk Management Perspective

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ABSTRACT:
This thesis investigates how complex projects such as Digital Twin (DT) enabled smart manufacturing industry based projects can face data interoperability failures and how those can be identified as project-level risks and managed proactively. The research foundations is based upon development of a Electric Vehicles (EV) Battery Health Management System (BHMS), where multiple engineering disciplines team exchange data across organizations having incompatible tools, standards, and organizational boundaries. Existing industry frameworks are exploring majorly "technical risk" aspects, however the project risk management aspect has been underexplored that classifies such failures under a generic label, obscuring the distinct root causes that require fundamentally different responses. A qualitative, literature-driven conceptual case study combined with innovative research based design science principles was adopted to analyze the delivery context of this project. Classic Project management tool has been explored and modified within the existing project risk management framework such as Work Breakdown Structure (WBS), Design Structure Matrix (DSM), and Risk Breakdown Structure (RBS). Those tools were experimented against a six-level interoperability taxonomy to decompose and figure out where and how reliability breaks down. Six distinct interoperability failure types were identified at specific stakeholder boundaries. The DSM analysis confirmed that every rework cycle in the BHMS case crosses at least one organizational boundary which establishes the fact that it is technically challenging to resolve interoperability failures independently as a team. These structural findings were later used to develop a three-phase Project Digital Twin (PDT) framework namely pre-deployment risk structuring, execution-phase monitoring through five project management based observable indicators, and level-specific response activation that replaces ad hoc investigation with targeted corrective logic. The framework is conceptual and has not been validated in a live project environment, which defines the scope for future empirical testing. The findings provide a framework establishing the fact that, interoperability risk can be made visible and required actions can be modified and adopted using standard project management instruments without requiring specialized data engineering expertise. This creates a foundation for more proactive, structured risk control in complex DT-enabled manufacturing projects.

Keywords: Digital Twin, Data Interoperability, Project Risk Management, Battery Health Management System, Design Structure Matrix, Smart Manufacturing, Socio-Technical Systems

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List Of Abbreviations

IR4	Industrial Revolution 4.0
IoT	Internet of Things
IIoT	Industrial Internet of Things
AI	Artificial Intelligence
DT	Digital Twin
OT	Operational technology
PLC	Programmable logic controllers
EV	Electric Vehicle
DIKW	Data-Information-Knowledge-Wisdom
PRM	Project Risk Management
PMI	Project Management Institute
PMIS	Project Management Information System
CPPS	Cyber Physical Production System

Chapter 1

Introduction

The Fourth Industrial Revolution 4.0 (IR4) has set a transformative epoch, pioneering and fundamentally altering the Industrial operation and technological integration process in different industries' landscape. Central to these transformative trends of industry are interconnected technologies such as Cyber Physical Production System (CPPS) or Industrial Internet of things (IIoT) (Soldatos et al., 2018, p. xxiii) that build a system or systems of systems (SoS) (Fortino and Savaglio, 2023, p.205) and operate cohesively through seamless connection of machines and physical devices with IT infrastructure(Soldatos, 2018, p.2) to facilitate enhanced operational efficiency through collaboration and integrated data-flows (Cavadini et al., 2018, pp.106-107) among various entities ; e.g. supply chain, design, service, maintenance (Gunasegaram, 2024, p.466).

Cavadini et al. (2018, pp.106-107) identify the digital manufacturing paradigm as a necessity that is market driven by addressing organizations' need for innovation, strategic direction of change from product-model to service-model by advanced integration of digital technologies and asserted that digital technologies play central role in value creation by promoting new industrial requirement of automation solution in the changed manufacturing industries landscape. Digital technologies facilitate organizations by increasing automation, eliminating error-prone processes, improving proactivity, streamline business operations, make processes knowledge-intensive, reduce costs, and increase smartness, ultimately achieving more with less (Soldatos, 2018, p.1).

Abanda et al. (2025) consider digital twin and IoT as essential enabling tool for digital transformation since significant benefits of digital twins are observed across different industries (e.g. Manufacturing, Construction). This thesis investigates the profound impact of Digital twin in manufacturing industry and how it impacts on Project Level Decision making specifically Risk Management. Often, the industry has adopted the term “Smart Manufacturing”. And many of the Authors Associated Smart Manufacturing as new dimension of manufacturing industry which was enabled by either “Industry 4.0” or “Digital Transformation”.

The subsequent section will highlight the problem statement, focusing on challenges that are induced at Project Level, particularly in terms of systems interoperability and co-ordination. The data from physical model or system that is accumulated through various sources are utilized to create digital twin model and systems . Hence, these integration of Digital Twin systems introduces challenges at the project level, particularly during system interoperability and co-ordination. These integration issues often manifest as risks during the project lifecycle. This study aims to explore how such risks are conceptualized by industrial researchers and how they are identified and managed throughout project execution.Additionally, case studies will be explored to review how can Project Managers ensure proactive decision making using digital twin technology during Project Execution. Based on that, I will create research question and objectives by identifying Problem statements. These research question will drive me towards building a comprehensive risk management strategy for Digital twin based Project Risk Management. This chapter will also cover the scope of study and limitation of research and also structure of thesis.

1.1 Background

Digital transformation under the framework of IR4 has enabled adoption of different technologies such as AI, IoT, Big Data Analytics, Cloud Computing(Florescu,2024, p.2) where DT by utilizing these technologies and its unique adaptation of creating virtual replicas of physical entities, is able to facilitate system optimization through the integration of real-time monitoring and control functionalities in complex dynamic requirement of manufacturing sector (Abanda et al., 2025, p.804; Li et al., 2025, p.1; Shao et al.,2019, p.2085). Manufacturers in such highly changing requirements in smart industries are compelled to rapidly develop high-quality products while facing complex constraints related to cost, time, and customer specifications (Chakrabortty et al., 2019, p.820 ; Goestch, 2015, p.3). Hence, such environment necessitates a focus on agility and resiliency to cope with global disruptions and volatile markets demand (Green,2023, p.736; Lazaro et al.,2018, p.28).

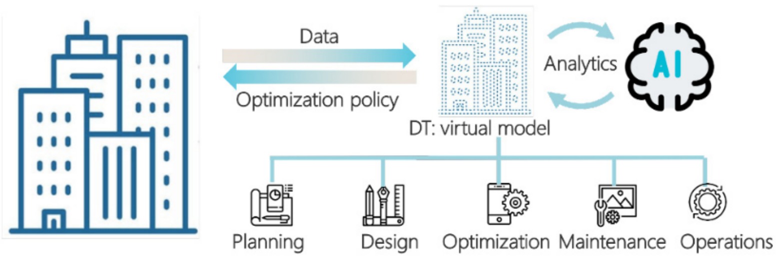

Figure 1.1. Illustrations of a representational Digital twin Model (Zhang, 2024, p.4).

Smart manufacturing project management is fundamentally distinct from its traditional counterpart since Industry 4.0 enacts technologies that increase computerization and interconnection of products (Abanda et al., 2025, p.823) in a demanding environment characterized by frequent uncertainties and high customer specifications(Chakrabortty et al., 2019,p.820; Rosen et al., 2015,p.567). Traditional manufacturing focuses on standardized processes that leads to mass-produced goods (Abanda et al., 2025, p.823), on the contrary advancement of digital technologies shifts the traditional business process as Egan and Tutos (2023, p. 859) discuss that in the era of digital age, profound rethinking of business processes is a necessity. Traditional production systems that relies on centralized automation architectures cannot utilize the fullest potential of system adaptability and flexibility in a market where mass-customization is a requirement due to increased product variety and shorter time-to-market(Calà et al., 2018,p.365). At the same time, manufacturers face the challenge of delivering such personalized products while maintaining low costs achieved through mass production as portrayed in Figure 1.2:

Brasche et al. (2023, p. 183) indicated that the traditional automation system is designed to support mass production at lower cost which is shown in the left side of the Figure 1.2. The

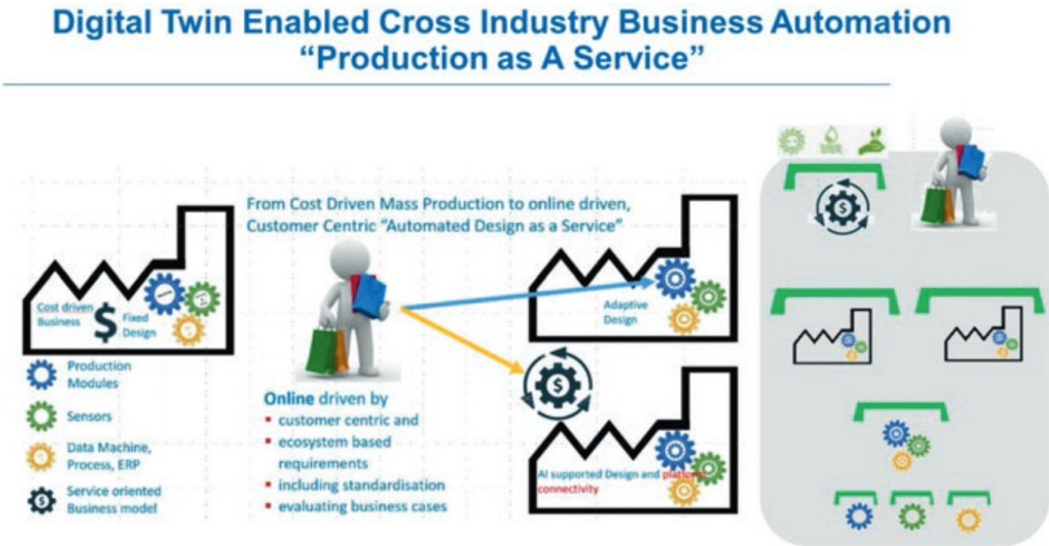

Figure 1.2. From cost driven mass production to online configured & customer individual production (Brasche et al., 2023,p.182).

authors highlighted that this model is rigid and lacks adaptivity, leading to an emphasis on the paradigm shift toward customization, where the customer starts acting as a co-designer of their product as shown in the middle part of the figure. Furthermore, the authors proposed a value chain ecosystem in Figure 1.3 which will be enabled through the digital twins of assets, machines, and services and implement service-oriented cost models that take into account the common value of ecosystems,

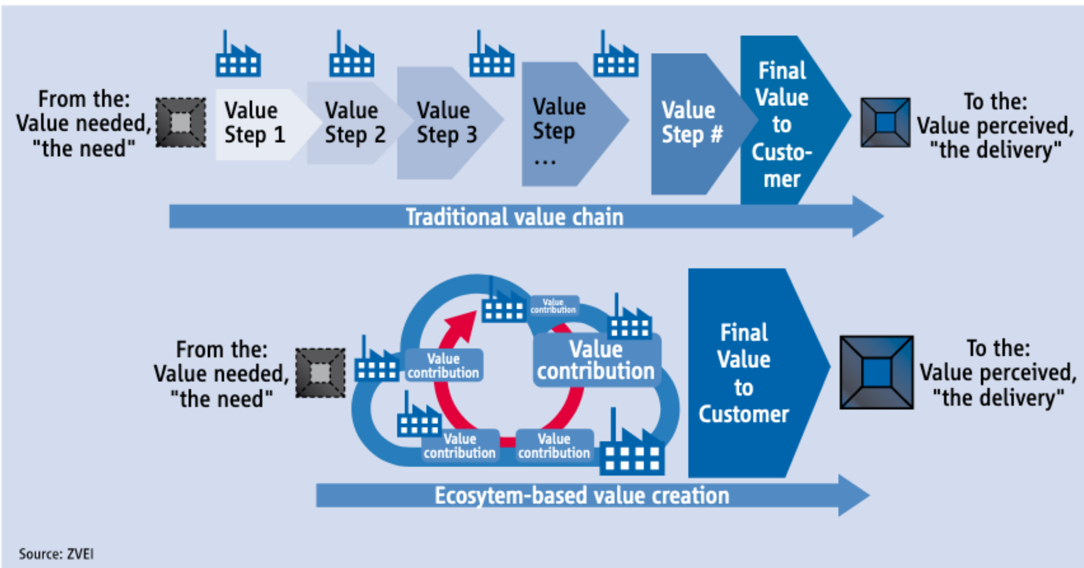

Figure 1.3. Optimal cooperative value aggregation in ecosystems (Zvei, 2021,p.30).

as opposed to existing cost models which focus on minimizing costs for individual suppliers is now being replaced by a highly interconnected model where value creation and costs are shared across an entire network of collaborating entities (Zvei,2021, p.30 ; Barni et al., 2018, p.348). Hence we can see a trend shifting from mass production towards mass customization.

As smart manufacturing industry by definition, is based upon technologies that are interconnected; hence it cannot succeed in an environment where functions of the organizations are siloed. As Grieves and Vickers (2017,p.108) emphasized that, they perceive three impediments namely: organizational siloing, knowledge of the physical world, and the number of possible states that systems can take; that hinder information sharing across system and contribute towards unsuccessful implementation of DT.

As DT performs significant role in the context of Industry 4.0 and Smart Manufacturing (Abanda et al., 2025, p.824), in another word successful implementation of DT is essential in ecosystem-based value-creation environment hence, project management requires a shift from traditional functional siloe of organizations toward a truly product-centric approach across the entire life-cycle. Here's why:

- **Understanding the Project Complexity:** According to PMBOK (2017,p.68) guideline, Complexity within projects is an outcome of the organization's system behavior(The interdependencies of components and systems), human behavior (The interplay between diverse individuals and groups), and the uncertainty at work in the organization or its environment also referred to as ambiguity (Uncertainty of emerging issues and lack of understanding or confusion). Additionally, the guideline also mentioned not to treat complexity as individual entity, rather it is embedded within project itself. Furthermore, PMBOK defined complexity as a characteristic or property of a project that is typically described as:
    - Containing multiple parts
    - Having numerous connections between the parts
    - Demonstrating dynamic interactions between the parts.
    - Exhibiting behavior that is produced as a resultant of those interactions that cannot

be simply defined as the simple sum of the parts (e.g., emergent behavior).

As elaborated by PMBOK, analyzing these factors that contribute to project complexity assists project managers emphasizing on critical areas for effective planning, management, and control to ensure successful project integration.

- **Product Complexity:** Contemporary Smart Products for instance electric cars, industrial machinery are comprised of multiple subsystems and components that is comprised of hardware, electrical and electronic component, and software domains(Kinman & Tutt, 2023,p.227) that often integrates IR4 technologies such as AI or ML. As the authors further evaluated that the challenge and complexity of product development increases proportionately with the sophistication of the product or system under development, for instance among all components as shown in Figure 1.4 of the EV, the battery pack is another subsystem where multiple components inside the battery are integrated.

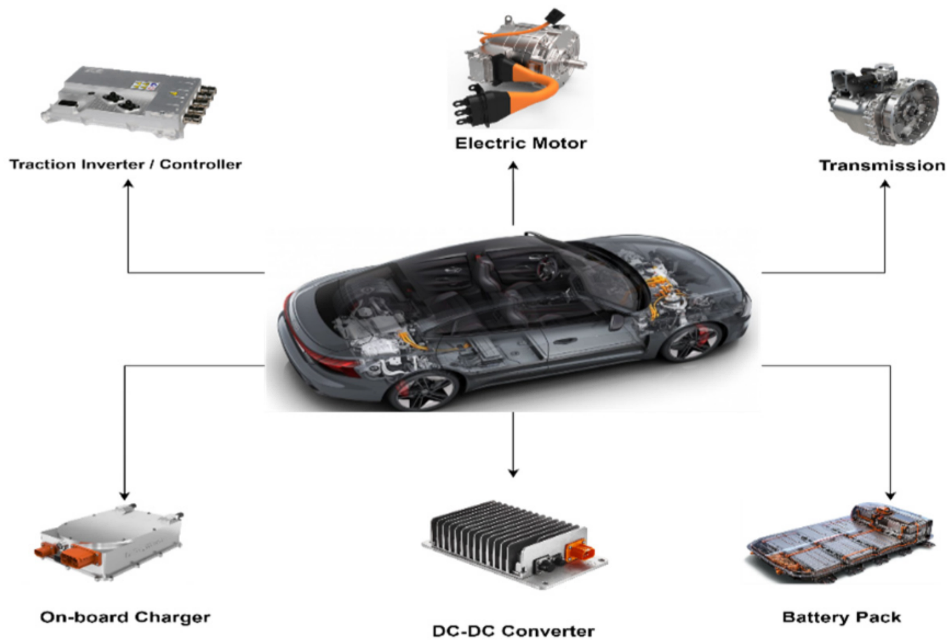

Figure 1.4. Main components of an EV propulsion drive system (Ibrahim et al., 2023,p.6).

- **Need for continuous integration and collaboration:** Achieving resilient CPS requires interdisciplinary collaboration, where engineers from multiple domains, institutions, and regions work in collaboration to conceptualize, design, develop, integrate, manufacture, and operate these complex systems(Rosen & Pattipati, 2023, p.604). In the automotive industries case, evidence of digital twin contributions towards end-to-end monitoring systems for automotive OEM has been documented by Kochhar(2023, pp. 782-783) where such systems are entirely data-driven and operate through a closed-loop process that integrates design, engineering, testing, production, sales and aftersales service assimilating the production to deployment process encompassing everything from embedded electronics to infrastructure. Through this proces, DT can integrate people, technology, and processes together, enabling more flexible and agile processes that helps maintaining complexity of project management as described earlier and shown in Figure 1.5:

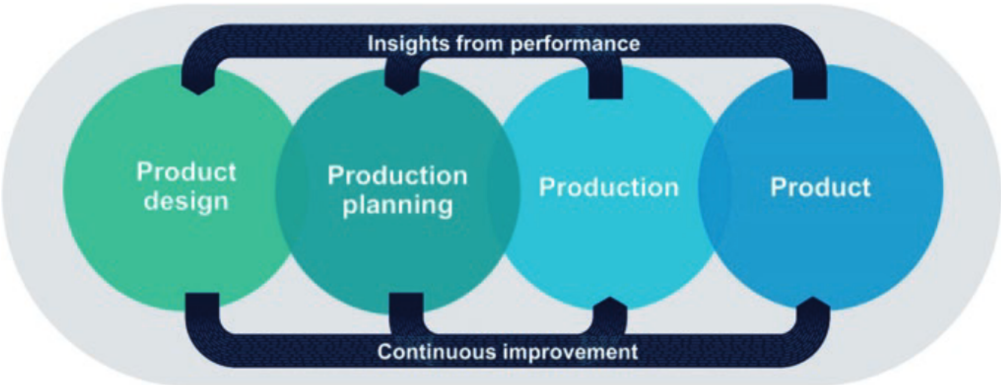

Figure 1.5. The comprehensive Digital Twin includes and supports the numerous lifecycle phases and respective models of actual product and process behavior (Kochhar, 2023,p.782).

The shift toward a truly product-centric approach ensures integration of data and processes across all enterprise functions across the entire lifecycle through comprehensive DT irrespective of functional area (Crespi et al., 2023,p.16; Margaria & Ryan, 2023, p.254; Grieves & Vickers, 2017,p.111)that effectively eliminates functional siloes (Kinman & Tutt,2023, p.231), treating projects as complex socio-technical systems involving continuous interplay among stakeholders, management, technical teams, and the supply chain, which is also referred to as interplay among its Product, Process, and Organization (PPO) components(Moser & Grossmann, 2023, pp.677,681).

As Moser & Grossmann (2023, pp.677-678) asserted that, project itself is considered a system and digital twin of a complex project design indicates whether teams and their work are synchronous or not, and identifies the behaviors and interactions between these systems and associate projects success likelihood. The statement exactly satisfies the requirement set by

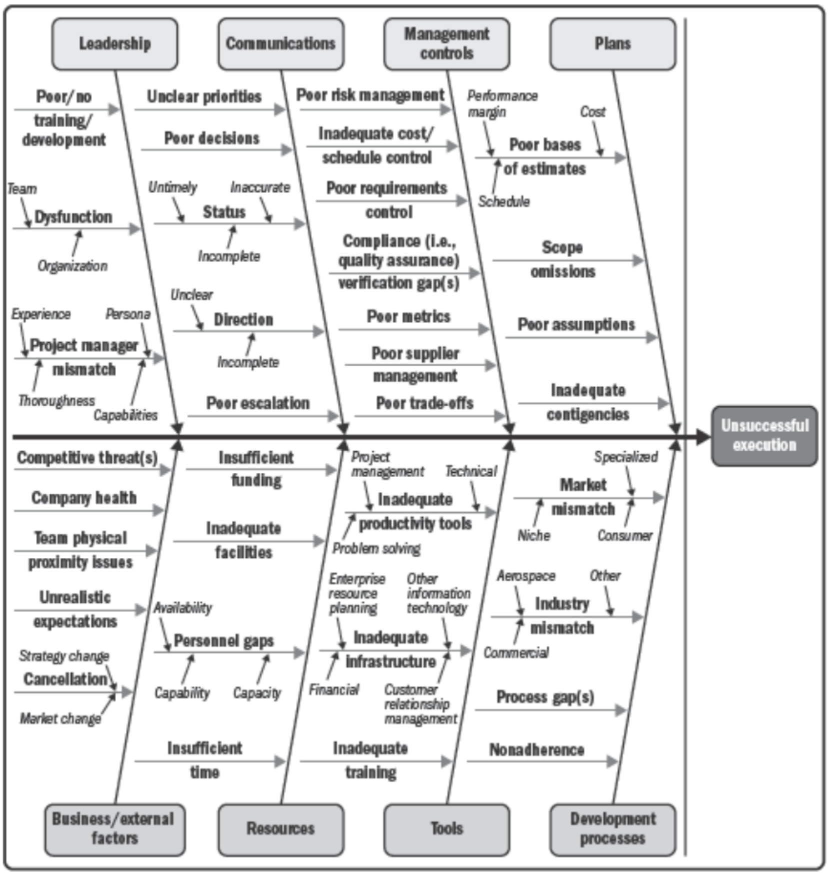

Figure 1.6. Causes of Unsuccessful Project Execution (Bissonette, 2016,p.73).

PMBOK regarding project complexity definition mentioned earlier. Hence, we can conclude that, project success relies not only on managing technical deliverables, but also on continuous co-ordination of dynamic interactions among stakeholders, technical teams, management, and supply chain to ensure that local actions remain aligned with systemic outcomes (Moser & Grossmann, 2023, p.680 ; PMI, 2017, p.54). In Figure 1.6, reasons of unsuccessful project execution has been shown.

1.1.1 The Problem Statement

DT data interoperability refers to the seamless integration and exchange of data between interconnected systems and components within a digital ecosystem (Margaria & Ryan, 2023, pp.253,256; Walli et al., 2023, p.550, Rosen & Pattipati, 2023, pp.654–655, Falekas et al., 2024, p.536). Its failure leads to project risk by introducing systemic inconsistencies and errors that propagate across linked systems and processes (Piroumian, 2023a, p.390), ultimately impacting project objectives such as schedule, cost, and quality. Since DT deployment involves complex, interconnected systems (Schmitt & Copps, 2023, p.37; Coupaye et al., 2023, p.338; Ozturk & Ozen, 2024, pp.362–363), the integrity of data flow is paramount (Falekas et al., 2024, p.536). When interoperability fails, the DT cannot provide a high-fidelity virtual representation of the physical asset or process (Schmitt & Copps, 2023, p.36; Piroumian, 2023a, p.384), directly undermining risk-informed planning and decision-making.

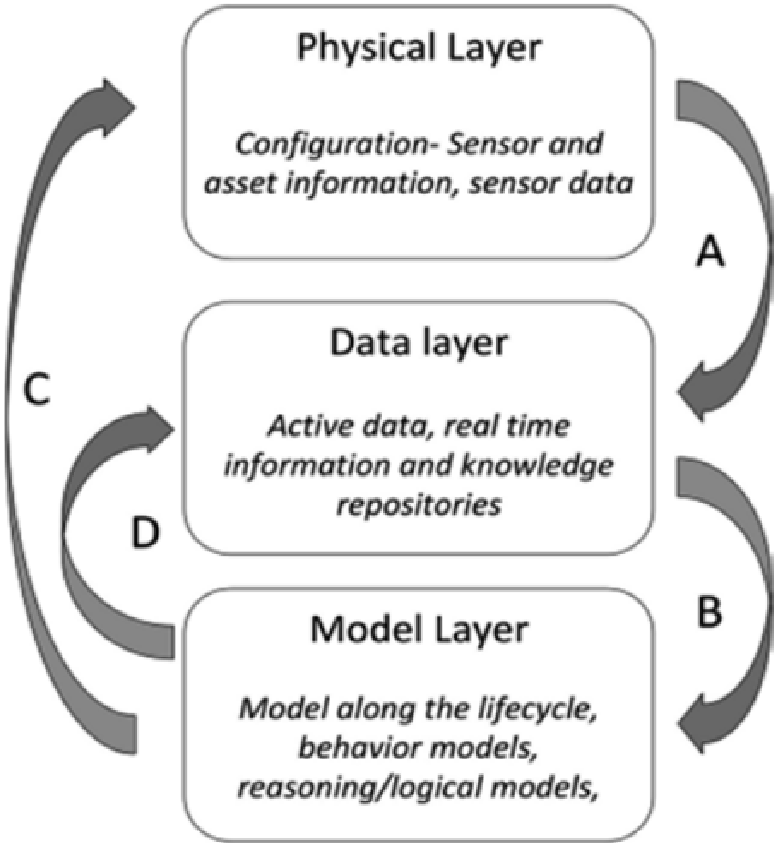

Figure 1.7. Information flow for a Digital Twin (Margaria & Ryan, 2023,p.261).

These challenges stem from a lack of unified standards and the heterogeneity of digital ecosystems (Abanda et al., 2025, pp.817, 826; Margaria & Ryan, 2023, p.258; Piroumian,2023a, p.387; Zheng et al., 2024, pp.52,62; Jost et al., 2024, p.221; Shvedenko et al., 2024, p.338; Gunasegaram, 2024, p.468). A major barrier to DT adoption in manufacturing and construction is the absence of a common definition or development standard, which hinders integrated application throughout the product lifecycle (Abanda et al., 2025, pp.816,817,826). In the manufacturing sector, data is often siloed and not integrated, thus necessitating complex data integration, data cleansing and data fusion issues (Margaria & Ryan, 2023,p.258). DT models are frequently developed by different stakeholders across project phases, and differing software versions further exacerbate interoperability problems (Abanda et al., 2025, pp. 817, 822). A digital twin of a complex system is often composed of components sourced from various vendors; when these lack compatibility, the DT system becomes untrustworthy or unusable (Piroumian, 2023a, p.388). Whyte et al. (2025, p.1) argues that, complex system not being entirely decomposible is one of the reasons why interdependences arise at the interfaces in complex projects. The authors further emphasized, when such changes occur, it creates repel effect by imposing significant risks at these interfaces since identification, managing and visualising systematic consequences of changes are challenging for system that also have multiple interdepencies as boundaries between design components, contracts and organisation coincide in such systems (as mentioned earlier, complex systems are composed of sources from various vendors). Responding to Project risk or risk management significantly becomes challenging due to such ambiguity. As Brahma & Wynn (2023,p.117) acknowledges that, design change can influence the course of information generated while executing product development process and the hierarchy doesn't follow any pattern since it can appear in any part of the process as depicted in Figure 1.8:

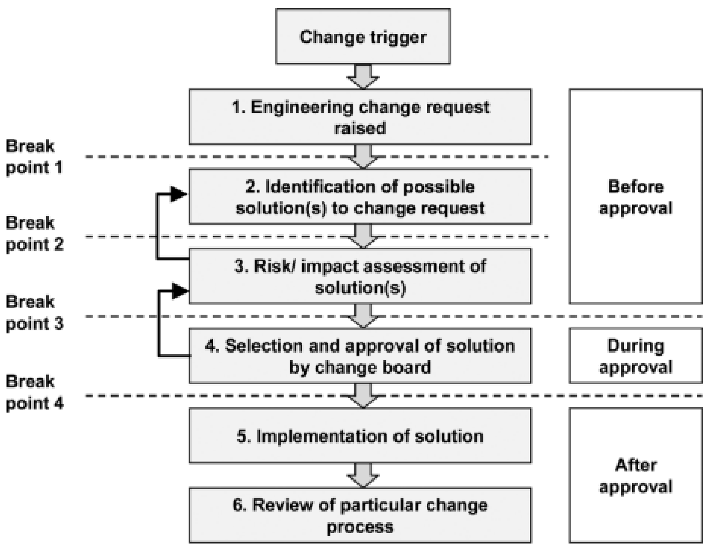

Figure 1.8. The Engineering Change process (Whyte et al., 2025,p.2).

Additionally, with support of multiple sources, Brahma & Wynn (2023,p.117) further clarified that, such design change is unpredictable and one aspect of design change can propagate throughout the system necessitating an entire change requirement throughout the whole system and such issues are more prominent in systems where multiple specialists or organization is involved.

Hence, engineering change management within such complex project has been identified as significant hurdles by multiple sources mentioned above, since major technical challenges or cases where factors like organisational boundaries and interdepencies exists across different engineering disciplines (Whyte et al., 2025,p.3), can impede the process as accountabilities in such cases become unclear or change in architecture is influenced due to emerging uncertainties & complexities in such systems.

This ultimately proves the point, that data interoperability in digital twin can influence decision making and hence if those issues are not acknowledged entirely, in the long run can propagate as a project risk. This statement is further clarified in the following Figure 1.9, where authors

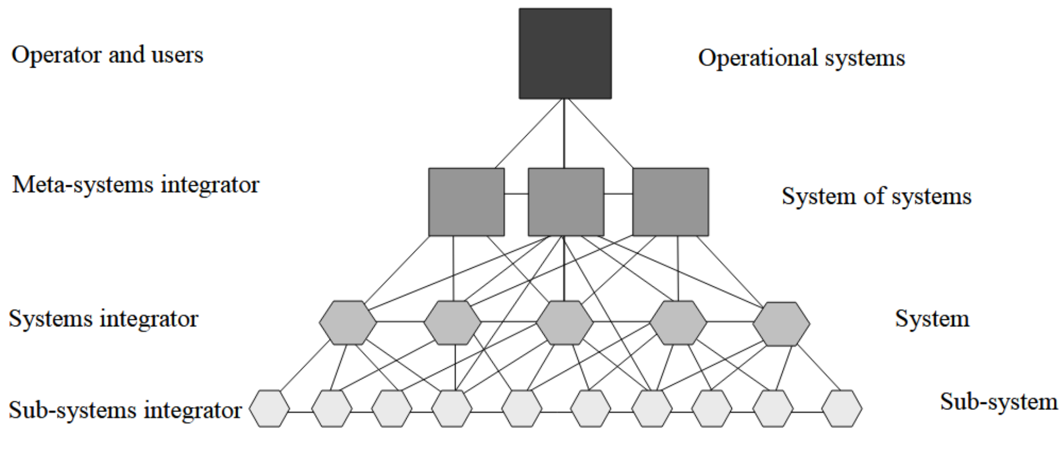

Figure 1.9. The different levels of systems integration within the complex interorganizational project(Whyte & Davies, 2021,p.4).

provided evidence that diverse knowledge and physical components are brought together both in the project's subsystems, systems, and system of systems and in their integration within operational systems and authors referred this term as system integration.

As outlined in the background section earlier in understanding project complexity section as per PMBOK, complexity in project manifests in various forms and not only limited to nonlinear system behaviors but also human interactions, and uncertainty arising from emergent issues are also included. Hence, complexity within project is not inseparable, rather the technological concerns of engineering and the organizational concerns of management must be addressed together within the project's delivery model.

Considering project as inseparable is supported by another literature. Whyte & Davies (2021,p.4) identified another concept namely systems integration as "the process of making constituent parts of systems that work together" where the distinctive focus lies on the actual systems that projects deliver. The concept presented here regarding project delivery model is based upon three foundations:

- **The Mirroring of System and Organization**: According to the authors Whyte & Davis (2021,p.), the architecture of a project's organization often "mirrors" the architecture of the technical system being built. There is a paradox of such system and organizational dependencies:

– "Organizational siloing" is identified as a primary obstacle to managing digital twin based complex systems (Grieves & Vicker, 2017, p.108). Functional areas (e.g., design, engineering, manufacturing) often possess separate, fragmented information sets. Because emergent properties arise from the interaction of these functions, management must actively span these boundaries. The systems integrator role is not just technical; it requires "boundary-spanning structures and activities" to bridge diverse organizational cultures and incentives This means if a project is broken down into modules or subsystems as shown in Figure 1.9, the organizational structure (teams, contracts) reflects those dependencies as . Therefore, managing the technical interfaces becomes indistinguishable entity of the organizational interfaces (roles, responsibilities, and contracts) that correspond to them. The authors presented several evidence of multiple inter-organizational complex projects (e.g. London Crossroad Rail Project, Berlin Brandenburg Airport in Germany) where tasks dependencies that were technical also influenced organizational failures. Hence, they proposed that these two domains "need to be combined" rather than distinguished and treated in isolation.

1.1.2 How Data Interoperability risks of DT creates risks in Complex Projects

Data interoperability issues, defined as the lack of standardization and uniformity in how different systems exchange and use data, compromise the fundamental integrity of the DT (Piroumian, 2023a, p.388). This failure translates directly into severe and cascading project risks that negatively impact execution across technical, cost, schedule, and quality domains in complex smart manufacturing projects since a project goal is comprised of schedule, scope and budget and must remain in equillibrium, also known as triple constraint (Marchewka, 2003,p.10). This failure translates directly into severe and cascading project risks that negatively impact execution across technical, cost, schedule, and quality domains in complex smart manufacturing projects. These risks can come in different form-

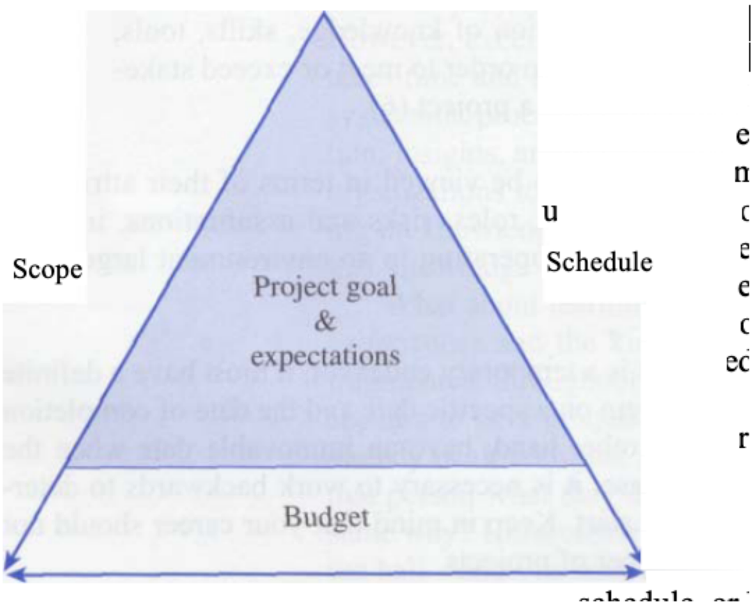

Figure 1.10. The Scope, Schedule, and Budget relationship-the triple constraint (Marchewka, 2003).

- **Risks via Error Propagation and Untrustworthy Data in Projects:** A DT system often consists of a composition of digital twin components from different vendors, tools, or development standards (Coupaye et al., 2023,p.338; Piroumian, 2023a, p.388; Rosen & Pattipati, 2023, p.604). If an upstream twin (e.g., DT A or DT B) inaccurately represents its physical counterpart, the error is inherited by downstream twins (e.g., DT C), and subsequently, this error propagates or cascades to DT D and so on. This means additional inaccuracies would amplify the degree of the errors at each juncture (Piroumian,2023b,p.390). Such dependency has been elaborated by Alam & Saddik (2017) In the Cloud-Based Cyber-Physical System (C2PS), every physical thing is accompanied by a representative digital twin (cyber thing) hosted in the cloud as shown in Figure 1.11, establishing a direct one-to-one connection between them.

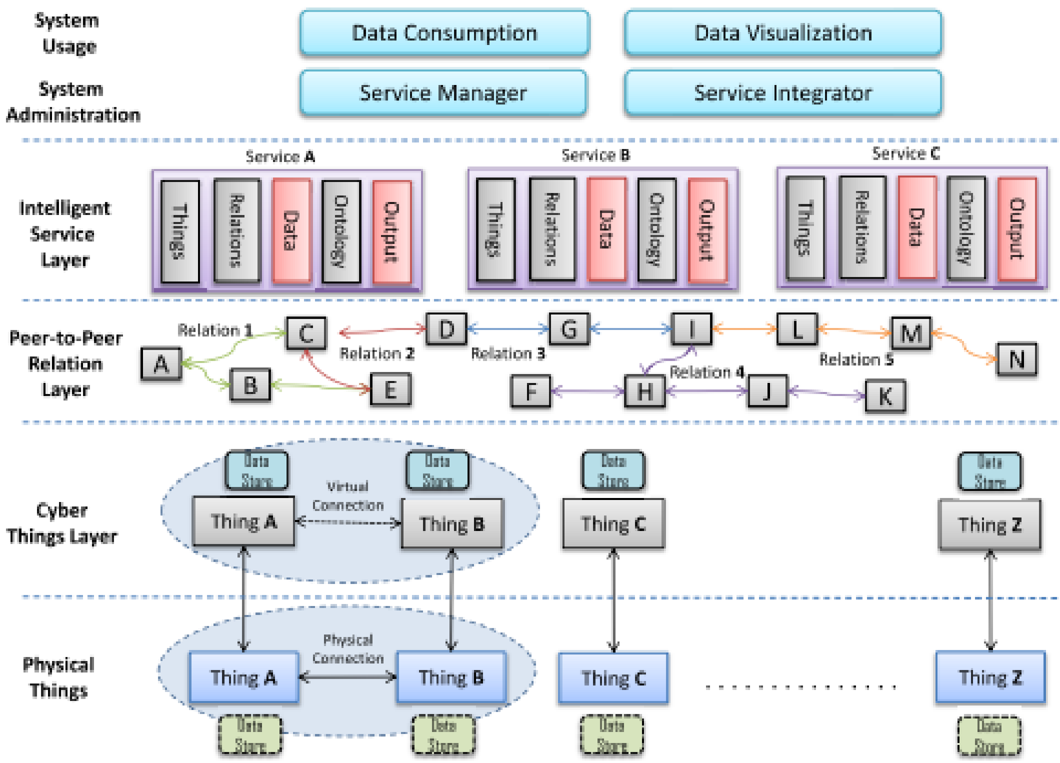

Figure 1.11. A Cloud based cyber-physical system architecture introduced (Alam & Saddik, 2017,p.2053).

This twin relationship ensures that whenever the physical world changes, its sensor attempts to update the current status to its digital twin, which can then process the data to notify the physical systems about the findings or send control commands (Alam & Saddik,2017, pp.2050,2053). Two physical things can establish peer-to-peer (P2P) connections through these cloud-based digital twin connections, which ensures scalability across the physical networks. Furthermore, complex systems as described further by this source suggest are formed through the hierarchical composition of lower-level digital twin things, where a higher-level master cyber thing acts as a hub and processes the event outputs of the lower-level subsystems to find regional or global knowledge (Alam & Saddik,2017, p.2058). A complex Digital Twin system can be structured like a hierarchy, where the top-level system (a "cyber thing" as mentioned by these authors) is built from smaller, lower-level digital twins or another way described, complex thing can also be organized as star networked topology (Alam & Saddik,2017, p.2058). Each lower-level twin represents a specific subsystem or component, and together, they form a complete system. This exactly clarifies that, the top-level twin or master system controls or coordinates these subsystems. So, if something changes in the top-level system, it reflects down to all the subsystems, and vice versa.

- **Fidelity & Trust Risk:** As the success of a DT is dependent on the integrity of the data provided (Piroumian,2023b, p.384), data synchronization is the paramount of DT's success that means data must be retrieved by a user- either a system or a human as described by this author and that user must be able to retrieve right kind of information and right detail associated with the software system and application platform of digital twin. If the DT loses fidelity to its physical counterpart, the system will be untrustworthy for such kind of decision-making (Margaria & Ryan, 2023, p.258). This risk means that the virtual representation cannot reliably simulate, predict, or optimize the production system (Kinman & Tutt,2023,p.230; Soori et al., 2023,p.1)

- **Modeling Accuracy Risks:** In manufacturing, data is often siloed and not integrated, which complicates data integration, cleansing, and fusion (Margaria & Ryan, 2023,p.258). Poor communication and the lack of common data standards among departments cause data inconsistency, which affects the development accuracy of the digital twin model (Abanda et al., 2025, p.822; Li et al., 2025,p.20).

- **System Suitability Risk:** If the DT model is inaccurate, it creates the risk that the final product or system will not meet specified quality standards (Rosen & Pattipati, 2023,p.608). For instance, prediction inaccuracies stemming from poor data fidelity can lead to failed compliance requirements or result in optimized strategies that do not align with actual production scenarios, weakening the efficacy of the DT technology (Li et al., 2025,p.20).

1.2 Purpose of the Study

Data interoperability issues significantly undermine the successful deployment of DT's in complex projects, as these challenges are exacerbated by the expansion of the DT ecosystem and the variety and heterogeneity of data that is typically fragmented and siloed across multiple vendors, domains, and systems (Margaria & Ryan, 2023, pp.258,270; Coupaye et al., 2023, p.338; Piroumian, 2023a, p.387; Zheng et al., 2024, p.62; Ying et al., Ying et al., 2024, p. 688). When multiple DT models are involved in a composite Digital Twin implementation, stakeholders may adopt different standards, protocols, and data structures, leading directly to interoperability issues at the data level (Zheng et al., 2024, p.62) , while the absence of a common language compromises the future interoperability of DT systems(Margaria & Ryan, 2023, p.256; Rosen & Pattipati,2023, p.650). Critically, this failure in interoperability or compatibility between DT components can render the overall system untrustworthy or even unusable, and if one component is inaccurate, the defect can propagate or cascade errors throughout the system (Piroumian, 2023a, pp.388,390).

For project execution, the lack of seamless collaboration resulting from data fragmentation leads to expensive errors and quality issues (Rosen & Pattipati, 2023, pp.633-634), requires costly rework to discover information that was already generated (Agostinelli,2024, p.427), and adds cost and delays due to reviewing and validating unreliable data handed over to operations teams (Mustard & Stray, 2023, p.707). Moreover, structural heterogeneity of data specifically hampers essential functions like real-time simulation and adjustment in processes such as assembly (Margaria & Ryan,2023, p.265), confirming that proper data interoperability is deemed a “make-or-break prerequisite” for the Digital Thread that binds the complex project together (Margaria & Ryan,2023, p.263).

While existing research on battery digital twins focuses primarily on the technical dimension such as modeling electrochemical behavior, predicting State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL)—this thesis shifts the emphasis toward the project delivery perspective. Specifically, it examines how system integrity issues such as data interoperability that arise during DT deployment can propagate into project-level risks affecting schedule, cost, and resource allocation. The study aims to develop and demonstrate a Project

Digital Twin framework that mirrors the BHMS development process using standard project management tools, including: Work Breakdown Structure (WBS) for project scoping, Dependency Structure Matrix (DSM) for analyzing task interdependencies and risk propagation, and

By doing so, the thesis seeks to show how project managers can utilize DT-enabled predictive monitoring capabilities (such as anomaly detection and early warnings) to make more informed decisions, anticipate potential disruptions earlier, and proactively control risks. Ultimately, the study contributes to bridging the gap between Digital Twin technology and project management practice in smart manufacturing, providing a framework that is both academically relevant and practically applicable for managing the risks of complex, data-driven projects like BHMS development.

1.3 Research Question and Objectives

Table 1.1. Research Questions and Objectives.

Research Question	**Research Objective(s)**
RQ1: How can data interoperability challenges in Digital Twin-based Battery Management System (BMS) development be identified and translated into project-level risks?	1. To identify key data interoperability challenges in the BMS design phase. 2. To analyze how these issues create project-level risks using structured planning tools such as Work Breakdown Structure (WBS), Design Structure Matrix (DSM), and Risk Breakdown Structure (RBS).
RQ2: How can a Project Digital Twin (PDT) support the monitoring and control of project-level risks caused by data interoperability challenges, and how can it be integrated into a comprehensive project risk management approach during BMS development?	3. To design a conceptual Project Digital Twin model that supports risk monitoring and control based on the risk categories identified in RQ1.

1.4 Scope and Limitation

This thesis focuses on managing data interoperability risks within Digital Twin-enabled EV BHMS projects, using a conceptual literature-driven case study grounded in real industrial research findings of Case industry X's whitepaper about digital twin implementation issues faced by organizations.

The research concentrates on the integration phase of a high-fidelity Digital Twin, specifically for an EV BHMS. The study examines the "merge bias" that occurs when heterogeneous data standards across different engineering disciplines (e.g., electrochemistry, embedded systems, and) fail to synchronize. By applying a Risk Breakdown Structure (RBS), the thesis translates these technical interoperability gaps into quantifiable project uncertainties such as schedule slippage and loss of system trustworthiness.

This research is grounded in the Socio-Technical Systems Approach, which posits that IT projects are planned organizational change rather than purely technical endeavors. Through this lens, data interoperability in the EV BHMS Digital Twin is not just an IT architecture flaw, but a socio-technical boundary issue. The failure of edge and cloud systems to communicate reflects the siloed social structures of the teams building them, making it a critical project management risk that must be addressed through structural integration tools. Your thesis contributes to smart manufacturing not at the micro level (robotics, factory scheduling), but at the macro level — ensuring that battery systems, data streams, and digital twins across the product lifecycle are interoperable, trustworthy, and predictive.

This thesis does not aim to build or simulate a technical digital twin model of an EV battery system (e.g., electrochemical or thermal simulations of SoC, SoH, or RUL). Instead, the scope is limited to examining how Digital Twin deployment impacts project risk management in the context of developing an Electric Vehicle (EV) Battery Health Management System (BHMS). The focus is on the project management dimension of Digital Twin adoption specifically, how system integration risks (such as data latency, synchronization errors, supplier/API dependencies, and resource bottlenecks) can be represented, analyzed, and mitigated using industry standard project management tools. Within this scope, the thesis will:

- Develop a Work Breakdown Structure (WBS) to structure the BHMS development process into manageable tasks and deliverables, highlighting risk-sensitive areas.
- Apply a Dependency Structure Matrix (DSM) to map interdependencies across tasks, showing how a failure in one component (e.g., data pipeline integration) can propagate into downstream delays (validation, compliance, deployment).
- Propose a Project Digital Twin risk monitoring framework that leverages the predictive capabilities of DT (e.g., predictive maintenance signals, anomaly detection, early warnings) to enhance project managers' decision-making for risk monitoring and control and build a risk management framework that integrates into the Lifecycle of the Project.

Limitations of the study include:

- **Technical scope limitation:** No attempt will be made to design or validate electrochemical models, cell degradation profiles, or thermal behavior of batteries. These aspects are well-covered in existing literature but fall outside the thesis' management perspective.

- **Data limitation:** The case study will be conceptual and literature-driven, supported by scenario assumptions rather than proprietary industrial datasets. Risk inputs for DSM will be based on published studies, expert insights from secondary sources, and scenario reasoning.
- **Organizational limitation:** The study does not evaluate organizational culture, policy, or real-time factory operations in detail, but instead focuses on the structural and methodological aspects of risk management in BHMS projects.
- **Generalizability:** While the case study is centered on BHMS development in the EV industry, the proposed framework may be generalizable to other smart manufacturing projects, but this will not be tested empirically within this thesis.

1.5 Structure of the thesis

- Chapter 1 will demonstrate the smart manufacturing industry case and its association with DT.
- Chapter 2 begins with how Digital twin has been enabled due to the Digitalization and integration of Digital transformative technologies. The chapter will further progress on the foundation what makes digital twin different tha traditional simulation technologies and connection of DT concept within Project Management domain from Manufacturing Industry perspective. The chapter will further outline How digital twin projects are defined (in the case of this thesis Socio-technical terms from literature review) and how to approach with Complex Projects in Engineering & Technology domain. Also Project risk management related frameworks and the Digital twin based Project risk management will be explored in detail.
- Chapter 3 will highlight the research methodology from Books and Selected Literature review where research methodology will be justified.

- Chapter 4 will highlight the case analysis and justify the research question and objectives with Qualitative analysis.
- Chapter 5 will highlight research findings.
- Chapter 6 will draw conclusions.

Chapter 2

Literature Review

In this chapter, discussions will be highlighted on Project risk management and later the connection between Digital twin and complex projects will be explored. Digitalization has been one of the core aspects of Industrial Revolution (IR4) and it has paved the way for digital transformation which has enabled technologies such as Digital twin (DT). Hence,it will be explored how Digital Twin systems have emerged as a breakthrough innovation that is empowered by the convergence of these emerging technologies, and are considered as pivotal enablers of digital innovation in constructing an intelligent, responsive, and highly adaptive industrial ecosystem.

2.1 Introduction to Project Risk Management

Risk is everywhere and management of risk is essential to stay competitive in Industry and uncertain global challenges landscape. Hence, specialized field like Project Risk Management (PRM) has emerged in Project Management domain. PRM is considered a critical component of successful project delivery. As Bissonette(2016,p.23) emphasized that, the distinction between a successful and unsuccessful project objectives is proactive employment of PRM by Project managers and their team. Consequently, it is essential to understand what impacts on Project performance. We can understand it through the definition of Project Risk. However, Raydugin

(2013, p.xxii) argues that the term uncertainty is not commonly used in Project management and risk in general is a vague term. Regardless of this argument, the author concludes that PRM by definition is essentially project uncertainty management, and its core role is described as enhancing the likelihood of project success.

2.1.1 Definition of PRM from Classical and Modern approach

Consequently, managing risk or uncertainty is considered fundamental across all Knowledge Areas including estimating, scheduling, procurement, and quality assurance(Bissonette,2016, pp.185,222; PMI,2017,p.72).The transition from classical to modern Project Risk Management represents a fundamental philosophical realignment in how risk is positioned within the project management system (Cooper et al., 2005,p.84; Raydugin, 2013, p.34). Classical PRM consistently produces the very conditions that cause complex projects to fail by treating risk as structurally isolated from the functions where exposure actually lives. It is executed as a compliance exercise at decision gates, disconnected from daily execution plans and never resourced into the operational work of functional teams (Raydugin, 2013, pp. 31,34,143,152). Modern PRM inverts this architecture entirely, mandating three-dimensional integration — vertical, horizontal, and in-depth so that risk ownership is distributed across disciplines and risk responses are operationally active rather than administratively dormant(Raydugin, 2013,pp.32,152, 161). This need for such risk framework implementation stems from the basic triple constraints of the project, namely cost (budget), schedule (time), and scope (or quality/performance) where these three objectives are inherently interdependent (Bisonette,2016,pp.43–44; Raydugin,2013,p.8). In the following Table 2.1, the difference between classical and modern PRM approach is discussed:

Table 2.1. Comparison between Traditional and Modern PRM (Marchewka 2003, Goestch 2015, Cooper et al., PMI, 2017).

Aspect	Traditional PRM	Modern PRM
Definition of Risk	Risk is defined narrowly as “the potential of loss resulting from a given action, activity and/or inaction” (Bissonette, 2016, p.41). Risk is expressed in terms of the degree of uncertainty that is associated with the possibility that project objectives will not be achieved which in turn may lead to detrimental impacts (Goestch, 2015, p.116).	Risk is referred to as “an uncertain event or condition, the occurrence of which, plays significant role in achieving project objectives by posing either a positive or a negative outcome”(Marchewka, 2003, p.170). Cooper et al. (2005, p.3) discuss two aspects in Project Management context where not only probability or likelihood of an event occurring is discussed, consequence or impact as a resultant outcome is also taken into consideration.
Scope of Risk (Levels)	Based upon individual risk events that impact project objectives.	Addresses both individual project risk and overall project risk (the effect of uncertainty on the project as a whole) (PMI, 2017,p.397; .
Primary Focus	Focused primarily on negative outcomes or events perceived as threats (Bissonette, 2016, p.41). Emphasizes on minimizing risks.	Maximization of probability and impact of positive events (opportunities) while adverse events (threats) is minimized (Marchewka, 2003, p.171; PMI, 2017, p.397).
Treatment of Positive Uncertainty	Since, only threats are perceived and it is often a common practise across organizations (Cooper et al., 2005, p.126), it often overlooks or ignores the management of opportunities(Bissonette, 2016, p.74) .	As PMBOK guideline intrinsically includes opportunities alongside with higher level threats mentioned, it additionally considers those in the response planning phase to exploit or enhance them (PMI, 2017, p.397), hence proactive risk mitigation is present.
Response Approach	As opportunities is not considered, classical PRM is often considered informal (Bissonette,2016,p.114) or reactive (Marchewka, 2003, p.168). Marchewka (2003,p.168) additionally discusses that, project stakeholders in such cases conduct risk management after a problem has occurred.	Defined as the systematic process of identifying, analyzing, and responding to project risk (Marchewka, 2003, p.171; PMI, 2017, p.395). It is a proactive management process.
Management Viewpoint	Classical PRM involves planning, identification(Goestch, 2015, p.117), analysis, responses, monitoring and controlling (Bissonette,2016,p.309), where risk management becomes standalone process(Raydugin, 2013,p.34), leading to more probable project failure outcome .	Risk management is considered integral to overall project management.It is presumed that, management tools and techniques have been developed already to reduce the likelihood of project failure.

2.2 Industrial Revolution 4.0 and Digitalization and its' connection with Digital twin Concept

Since the Industrial Revolution 4.0 (IR4), Industries are adopting more automation and going through digital transformation. Industry 4.0 empowers digital transformation and provides on-demand services with high reliability, scalability, and availability in a distributed environment (Aheleroff et al., 2021,p.3). According to Semeraro et al.(2021,pp.1-2),before the industrial revolution 4.0, the production in shop floors heavily relied on physical space due to which it often led to lower efficiency, accuracy and transparency. The authors also highlighted a paradigm of technology such as computers, simulation tools, Internet and wireless networks that facilitated a virtual space for parallel operation within the system for virtualizing physical assets and remote monitoring opportunities.

Khan et al. (2017,p.3) argues that, although Industrial revolution 4.0 do not have concrete definition, the foundation of this concept is based upon six principles which is demonstrated in Figure 2.1:

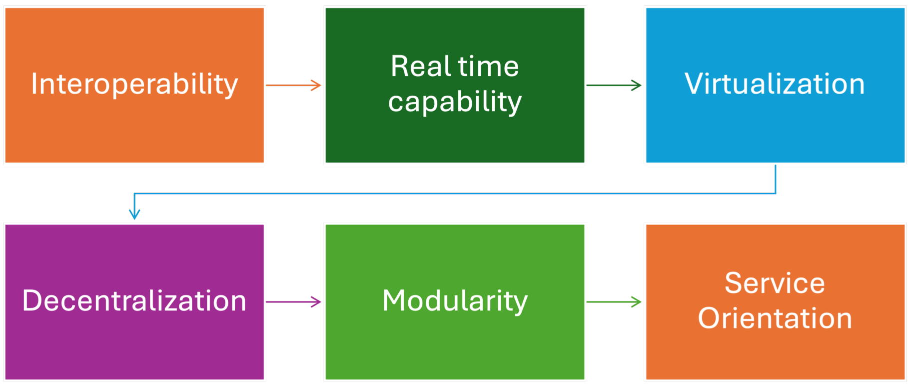

Figure 2.1. Foundation of Industry 4.0 concept (Modified & Adopted from. Khan et al. (2017)).

Some of the research articles that I have reviewed, echoes the same concepts of six principles as "Design foundation" of the term Industry 4.0. In the following Table 2.2,the concept definition explored by different authors will be presented:

Table 2.2. Six Design Principles of Industry 4.0 According to Key Authors (Khan et al., 2017; Saldivar et al., 2015; Moshood et al., 2024).

Principles	Author Name & Publication Year	Statement	Attributes
Interoperability	Khan et al. (2017)	“The ability of communication among CPS, IoT devices, factories and human via IoT, IoS and IoE” and “It integrates the classical systems with the modern models.”	Communication
	Saldivar et al. (2015)	Includes Interoperability as a design principle for CPS, IoT, IoS, and Smart Factories.	Connectivity
	Moshood et al. (2024)	“Widened communication across technology and humans” via CPS and IoT.	Communication
Real-time Capability	Khan et al. (2017)	“Collecting and analyzing data to detect failure and find alternative solution to handle the problem for speedy production.”	Responsiveness
	Saldivar et al. (2015)	Design principle crucial for Smart Factories.	Monitoring
	Moshood et al. (2024)	Defines it as locating problems using real-time data.	Problem Detection
Virtualization	Khan et al. (2017)	“Virtualization of physical processes monitored by CPS for simulation and virtual plant models.”	Simulation
	Saldivar et al. (2015)	Design principle for CPS and Smart Factories.	Simulation
	Moshood et al. (2024)	“Visualization and simulation of real-world activities in a digital environment.”	Visualization
Decentralisation	Khan et al. (2017)	“The ability of CPS to take decisions independently in distributed environments without central command.”	Autonomy
	Saldivar et al. (2015)	Applicable design principle for Smart Factories.	Decision-making
	Moshood et al. (2024)	Enables CPS to make autonomous decisions without central control.	Autonomy
Modularity	Khan et al. (2017)	“Capability of quickly adding new processes, machines, and modules.”	Scalability
	Saldivar et al. (2015)	Design principle for IoS.	Flexibility
	Moshood et al. (2024)	Same as Khan’s: flexibility to add modules quickly.	Scalability
Service Orientation	Khan et al. (2017)	“Facilitates decision-making for managers, operators, and consumers by using services connected to CPS.”	Decision Support
	Saldivar et al. (2015)	Defined in IoS systems.	Service Architecture
	Moshood et al. (2024)	Decision-making via CPS service integration.	Decision Support

2.2.1 Factors that Influence Digitalization Process

- **Complexity Across Enterprise:** With each Product or Process and Multiple Departments that have siloed information within an organization will eventually face complexity in terms of Product development, manufacturing process or getting valuable insights from data since they are not connected and stored in an organized manner. Digital transformation can provide holistic data-centric operation instead of relying on domain-centric siloed information. Hence, Companies want to manage this complexity by enabling digital transformation which facilitates widespread digitalization of process, data flows and methodologies and integrates all parts of the business and turn data into value at every stage of the product and production lifecycles: design, realize and optimize; the process however is a continuous optimization endeavor to achieve the digital enterprise by leveraging data and IoT insight from the product lifecycle, connecting and maintaining integration from silicon to infrastructure, assigning requirements and act on phases for deployment, from design to manufacture, and using the real and digital worlds in sync for creating value(Kinman & Tutt,2023, p.229).

- **Change of Strategic Landscape of Market Demand:** Customer demands are variable and they want product that fulfills specific use case, hence companies are constantly on the move to innovate and manage global complexity. However, this trend has shifted from mass production to mass-customization and demand driven product models.Hence, the trend is leaning towards more adaptable and dynamic configurable manufacturing solutions such as Made-to-Order(MOT),Configure-to-Order(CTO) and Engineering-to-Order(ETO) from the conventional Made-to-Stock production models(Soldatos,2018,p.4).

- **Technological Advancements:** The ongoing development of New IT trends has facilitated communications, processing, storing, and sensing capabilities and has paved the way towards digital transformation initiative. Innovations in wireless connectivity, radio frequency technology, and micro-electromechanical systems have spurred the creation of affordable, compact sensors, micro-controllers, and RFID systems, which, combined with Artificial Intelligence (AI), signal processing, distributed computing, and big data, have deeply reshaped industries within just two decades (Fortino &

Savaglio,2023,p.206).

- **Integration of Technologies:** The integration of various digital technologies into real-world applications, processes, products, and services.Cloud and edge computing facilitates flexible and automatic distribution of computing capacity by transferring control functions to the cloud.

- **Shift towards Predictive Maintenance:** Building Physical prototypes are expensive and simulation is the way to save manufacturers time and avoid costly breakdown of physical materials. As mentioned earlier, higher level of softwarization and IT infrastructure has provided flexibility and adaptibility and it no longer requires rigid hardware-centric dependency. The facility also extends towards design change for building prototypes or simulate plant scenario of failures. Hence, industrial organizations want to deploy preventive maintenance so that they can avoid the catastrophic consequences of unplanned downtime and prepare in advance for unpredictable circumstances. Tools and components are replaced at scheduled intervals prior to their estimated end-of-life.Predictive maintenance offers industry to exactly schedule maintenance when it is required, not before or after oppose to reactive or preventive strategy offering an edge in **Overall Equipment Efficiency (OEE)**, enabling accurate prediction of parameters such as the **End-of-Life (EoL)** and the **Remaining Useful Life (RUL)** of machines and their parts(Soldatos,2018,p.6).Predictive maintenance is usually based on the collection and analysis of large digital datasets about the condition of the equipment for instance, data from vibration and thermal images,energy consumption data,acoustic and ultrasonic sensors as well as quality data that can be retrieved from enterprise systems. Hence, predictive maintenance highly dependent on the efficiency of Big Data and Artificial Intelligence capacity in the industry, specifically which is highly relevant in this manufacturing industry.

- **Societal and Regulatory Shifts:** There is a push for greater safety, sustainability, and equity in human mobility, particularly evident in the automotive industry's focus on vehicle electrification and autonomy. New environmental regulations also call for reduced carbon emissions, further driving the need for digital solutions

2.2.2 Reason of Organizations leaning towards digitalization and Emergence of Digital twin Concept

The reason why organizations are adopting digitalization has relevance to the reason why digital twin has been utilised in Project. In earlier section, transition trends of higher level of softwarization from conventional OT has been discussed.The Higher level of softwarization and conventional OT concept will be explored further:

- **Shifting towards Cyber-physical based Production System:** Conventional OT has historically relied on **Programmable logic controllers (PLCs)** and the "classical automation pyramid." Although these systems provided stable and repeatable processes for industrial operation case, Lazaro et al. (2018,p.47) argues that these systems are inherently rigid and communication is restricted to specific layers and complex interfaces required for cross-layer interactions. Current PLC technology, which dominates the deployment of industrial automation applications, is a legacy of the 1980s, unsuited for sustaining complex "system of intelligent systems" functional architectures (Cavadini et al.,2018,p.110). Hence, Conventional OT offered limited flexibility in adapting to rapidly changing manufacturing demands.

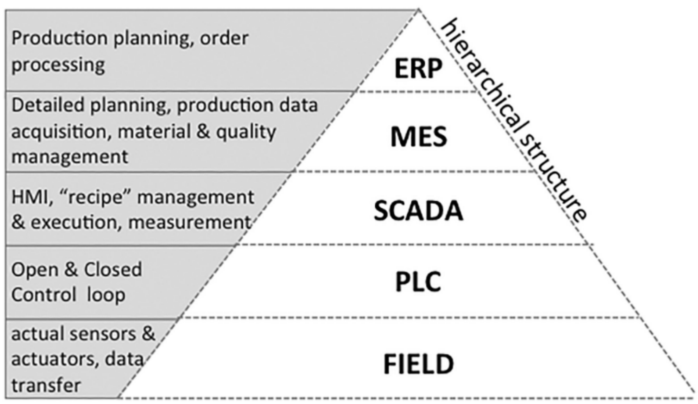

Figure 2.2. Classical automation pyramid representation (Cavadini et al.,2018,p.105).

However, there is an alternative proposition regarding this classical automation pyramid approach. The question arises, if traditional automation pyramid can solve the requirement of production system already with a stable operability, why do we need to have new manufacturing trends that supports this dynamic and flexible operation approach in a new cyber-physical based production system? As Lazaro et al. (2018, pp. 28-29) emphasizes that, planning and production system has been influenced by three factors (e.g. flexibility, productivity and plateaued trends of predictability of processes) and alongside of this traditional automation pyramid system,creation of shorter response time can contribute to the requirement of production system by adoption of rapid responsiveness, enhancement of product quality and production at lower cost as depicted in Figure 2.3:

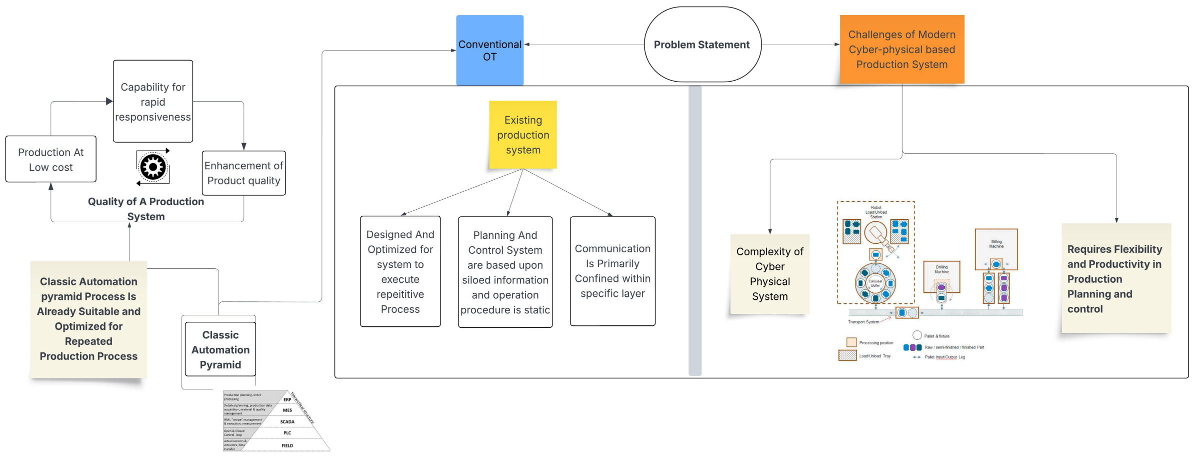

Figure 2.3. The need for new manufacturing trends for Cyber-physical based System (Modified & Adopted from Cavadini et al., 2018; Lazaro et al., 2018; Rosen et al.,2015).

- **The need for Autonomous Decision-making:** To utilize the full potential of shorter response time, it is essential that processes remain highly transparent and that information is delivered reliably and accurately on demand in the accurate location and time and the operation remains independent of human input (Lazaro et al., 2018, p. 29).

- **Autonomus functionality enables at Cyber layer:** In a smart manufacturing industries context, manufacturers want to predict and design operations utilizing simulation tool before making even physical prototypes. Since Industry 4.0 applications are based upon Cyber-physical systems (CPS) (Mendoca et al., 2022, p.2; Kefalakis et al., 2018, p.270; Lazaro et al., 2018, p.27), one of the core characteristics is that,automation functionalities is applied at cyber layer of the production system. (Kefalakis et al., 2018, p.270).

Unlike physical environments, where mistakes can be costly and only fixed operation can be executed, which limits the opportunity of flexible experiment, plant operators can modify digital world operations through simulation and it can be executed at a low cost. This opportunity further facilitates what-if scenario testing allowing them to optimize and deploy the most effective configurations for automated operations,by utilisation of Industrial Internet of Things (IIoT) tools (Kefalakis et al., 2018, p.267). Hence, by utilization of virtual plant models to test and simulate automated operations is commonly referred to as ”digital twin,” a fundamental key enabler for the digital transformation of manufacturing processes (Kefalakis et al.,2018, p.268).

Hence, advanced computational and data processing capabilities, which are essential for autonomous functionality and its dynamic configuration, are primarily enabled and concentrated at the cyber layer due to the nature of the technologies involved. Here’s why cyber layer is central to autonomous functionality:

– **Advanced Computational Resources:** The cyber layer is characterized by its use of scalable and distributed computing technologies, such as Cloud processing and storage, Big Data analytics, machine learning (ML), and deep learning (DL) and these technologies provide the necessary computational power to build dynamic data models and enable capabilities like diagnostics, prognostics, risk management, optimization, and predictive analytics (Aheleroff et al., 2021, p.2). This form the basis of autonomous behavior.

– **Decision-making and control:** Tao et al.(2019,p.655) presented his model of mapping between physical and cyber/digital world. The cyber layer is

  responsible for analyzing state information (Qi et al., 2021, p.12) from the physical part; which is also referred to as Manufacturing resources (e.g. human, machine, material, environment)(Tao et al., 2019, p.655), generating control commands, and making decisions that are then fed back to the physical layer for execution(Qi et al., 2021). In manufacturing, this layer incorporates smart data management, analytics, and ubiquitous apps and services that enhance productivity. Through this close interaction, the cyber part processes and evaluates data in real time, while the physical part senses and executes these decisions. For instance, digital twins in the production

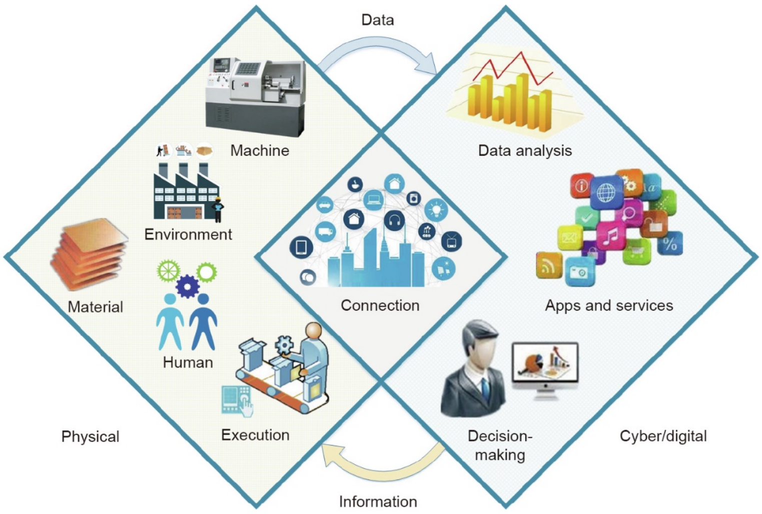

Figure 2.4. Mapping Between Digital and Physical World (Tao et al.,2019).

phase can autonomously evaluate performance, optimize resource allocation, and support operational planning.

2.3 Project Risk Management Concept in Complex Technology Projects: A comparative theoretical approach

The execution of complex technology projects encompassing Information Technology (IT) systems, research and development (R&D) initiatives, and advanced engineering designs inherently involves profound uncertainties (Goetsch, 2015,p.1; Teller et al., 2014,p.68).This challenge is particularly acute in technology projects involving novel deployments, where Goetsch (2015,p.117) identifies "insufficient maturation" as a primary risk driver. Projects that operates on the low end of the learning curve with untried processes (Goestch,2015,pp.117,119) systematically harbor latent defects that only surface at integration points. Cooper et al.(2005,pp. 63,66) further identifies this "Integration and interfacing" as a primary technical risk driver. They classify this risk as highly likely when there is Major integration and interfacing required, never done before or when it involves "Major integration with R&D" making them structurally incapable of being identified through classical risk identification methods alone.

Two foundational approaches that emerge prominently across the literature are:

- Technical/Engineering-Centric Approach to Project Risk Management
- The Socio-Technical Approach to Project Risk Management.

These two approaches differ fundamentally in how they frame the nature of project risk. A purely technical approach focuses narrowly on the tools, techniques, and methodologies of technology development, whereas a socio-technical approach dictates that equal attention must be paid to the organizational side, active stakeholder participation, and user involvement. The technical/engineering-centric tradition defines risk broadly as the "probability that things will not go as planned and that unplanned events will occur and have a detrimental effect on a project's success" (Goetsch,2015,p.116). While this definition is not confined to technical events, the methodological apparatus of this tradition such as its Risk Breakdown Structure (RBS), quantitative scoring tools, and primary risk categories is predominantly oriented toward engineering execution contexts (Goetsch,2015,pp.116–121;Marchewka, 2003, p.170). Within this framework, organizational and human factors are explicitly treated as a parallel category (specifically classified as "Internal—Nontechnical" risks that grow out of human and organizational issues) rather than as structurally inseparable from the technical risk landscape (Goestsch,2015,pp.119-120). Before proceeding towards further explanation about PRM framework of complex projects, the figure shows the core idea of each concept in Figure 2.5: In

the Table 2.3, the theoretical framework for PRM that is applicable for complex projects is further explored: PRM in complex technology projects has been theorised through two complementary analytical lenses — a Process/Analytical tradition (PMBOK, Goetsch, Raydugin, Cooper) that provides the procedural and mathematical backbone of risk management, and a Socio-Technical tradition (Bissonette, Marchewka) that provides the contextual and interpretive framework for understanding where risks originate and why they propagate. The former tells you how to manage a risk once identified; the latter determines whether you identified the right risks in the first place. For a thesis about data interoperability — a problem that is simultaneously a technical integration failure and an organisational boundary failure — the Socio-Technical tradition is not one option among three. It is the necessary frame for seeing the problem correctly, within which process and analytical tools then operate.

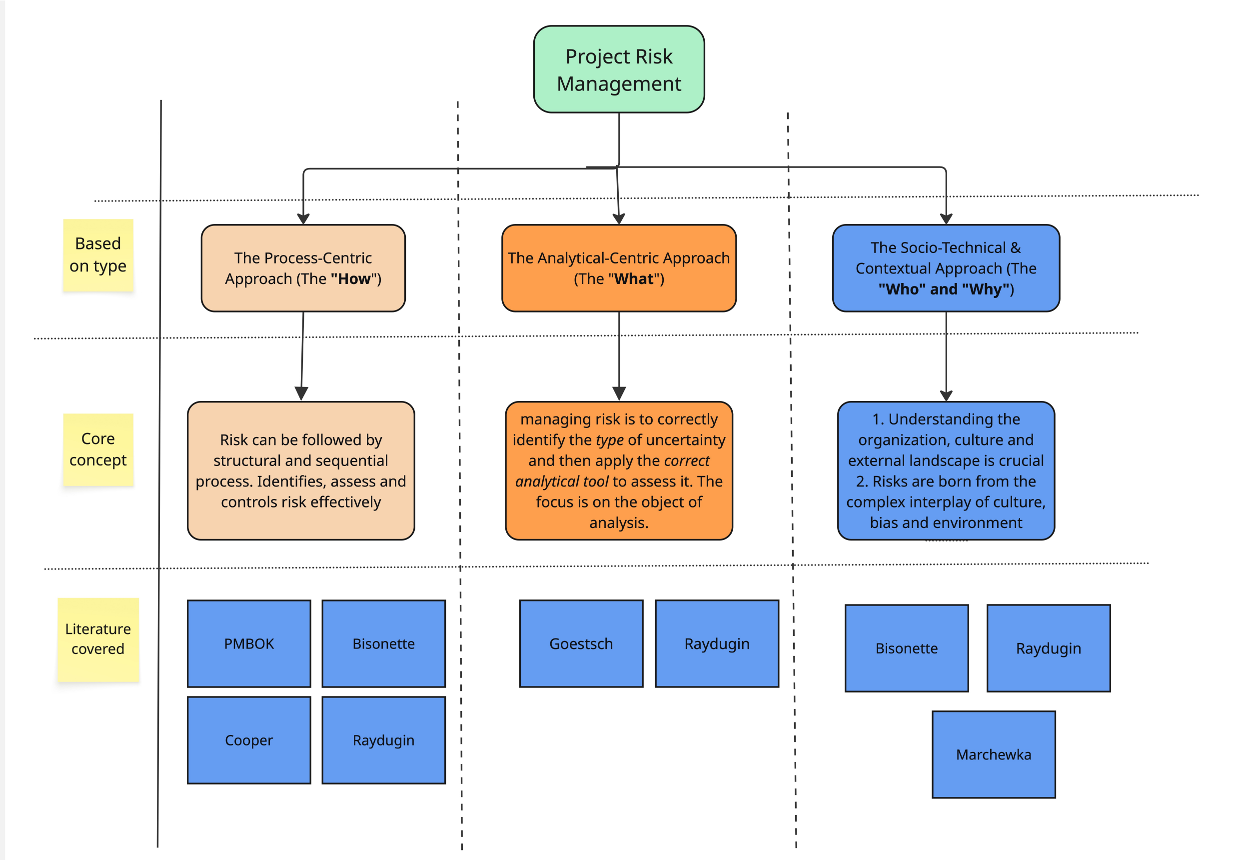

Figure 2.5. PRM theoretical framework explored in Reviewed Literature (Reviewed from Bissonette, 2016; Cooper et al., 2005; Goetsch,2015;Marchewka,2003; PMI, 2017; Raydugin,2013).

2.3.1 Digital twin in Complex Project Management

The requirement for a DT in complex project management (PM) arises from the insufficiency of traditional PM approaches in handling the profound complexity involved in project, dynamic uncertainty, and real-time data dependency which are inherent in modern, large-scale projects, particularly those involving CPS in manufacturing and construction. Some of the limitations of traditional PM approaches are:

- **Static data:** Traditional PM approaches are insufficient, as they often rely on methods with a limited vocabulary for representing project realities (Moser & Grossmann, 2023,p.683), utilize tools that function only with static data (Florescu, 2024, p.3).

- **Simplistic Scheduling Models:** Classic approaches, such as Gantt charts, Line of balance charts (common in construction industries), and networking models like PERT(Program Evaluation and Review Technique)/CPM (Critical Path Method) (Moser & Grossmann, 2023, p.683; PMI, 2017, p.175), rely on fixed durations or three static point estimates (Raydugin, 2013, p.73), and fail to capture complex systems in their dynamic evolution (Florescu, 2024, p.). Hence, PERT/CPM is not appropriate for analyzing projects with overlapping or interdependent tasks because of it's inability to model information flow or loops (Gálvez et al., 2015, p.72). As such, project models that require representation of human and non-human agents, their dynamic interactions, resource contention, rework, and communication factors cannot be modeled as project using classical method due to their limitation and hence lacks dynamism. Classical models assume resources are often interchangeable, replenishable, and lack agency, which avoids the real-world dynamics of human teamwork (Moser & Grossmann,2023, p.683). Such interplay between digital models, analytics and data alongside with real world outcome, decision and action is portrayed in Figure 2.6. As explained by these authors,both real world entity and its virtual projection model produces project data and these are the foundation of exploration, insights and decision making.

The DT provides additional and necessary benefits over classical simulation tools and traditional PRM techniques because it represents a sophisticated concept characterized by real-time bidirectional data exchange between the virtual model and the physical counterpart. Real-time synchronization and bidirectional data flow are the key differentiators between a DT and traditional simulation or digital models (Aiello et al., 2024, p.516; Kostrzewski, 2024, p.728; Shao et al., 2019, p.2087 ; Wynn & Irizar, 2023, p.2).

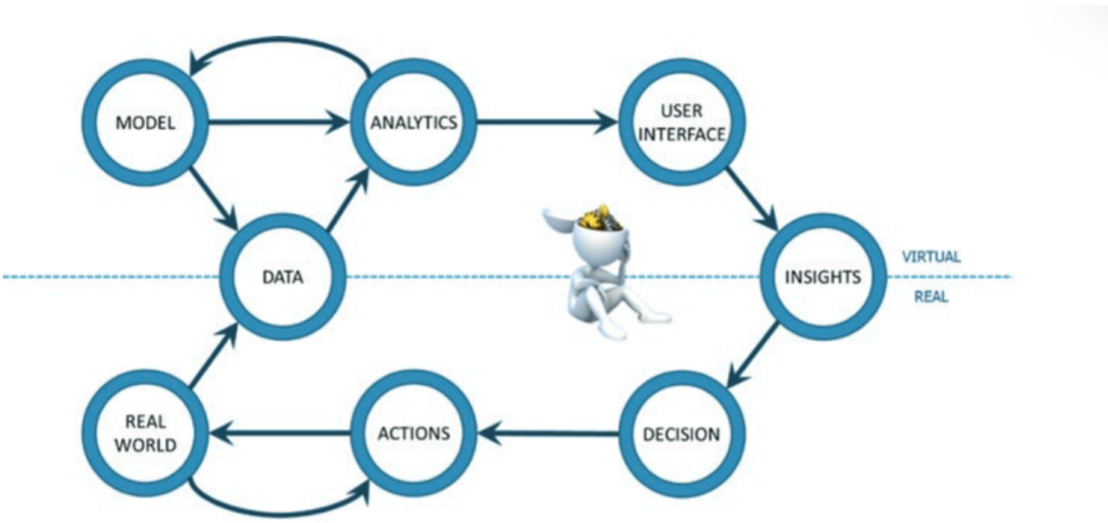

Figure 2.6. Digital Twins of complex systems projects (Moser & Grossmann, 2023,p.682).

The need to shift from **reactive to real-time risk management** in smart manufacturing project arises because Industry 4.0 environments, characterized by complex ecosystem-based value creation and high interconnectivity, are dynamic and prone to unpredictable, undesirable emergent behavior (Brasche et al., 2023, p.187; Goetsch, 2015, p.116; Grieves & Vickers, 2017, p.86; Rosen et al., 2015, p.567; Schmitt & Copps, 2023, pp.44-45; Uribarri et al., 2018, p.394; Whyte et al., 2025, p.1; Zhang, 2024, pp. 6-7). Traditional risk management, relying on retrospective analysis, is insufficient because the speed of autonomous, reconfigurable production systems means that time-consuming assessment approaches become obsolete when changes occur instantaneously (Uribarri et al., 2018, p.397).

The DT is crucial in facilitating this transition to proactive and responsive risk management because it acts as an artificially intelligent virtual replica of the physical system, enabling simultaneous and iterative development that integrates downstream concerns early into the design phase (Rosen & Pattipati, 2023, p.599; Grieves & Vicker, 2017, p.98; Soori et al., 2023, p.1). DTs mitigate risk by allowing teams to simulate and test different scenarios and evaluate the impact of changes virtually, thus reducing development risks related to cost and schedule (Piroumian, 2023b,p.369; Rosen & Pattipati, 2023, p.614; Mustard & Stray, 2023, pp. 706–707; Green, 2023, p.766). Furthermore, DTs, often enhanced by AI/ML and connected via the Digital Thread (Kinman & Tutt, 2023, p.240), provide real-time monitoring of physical assets (including equipment health and performance) and processes, providing prognostic capabilities that predict future failures or undesirable states (Zhang, 2024, p.7 ; Minerva et al., 2023, p.303 ; Gunasegaram, 2024, pp.461,465; Shao et al., 2019, p.2087; Soori et al., 2023, p.6). This continuous, model-assisted feedforward control approach, rather than reactive feedback controls, allows decision-makers to identify issues before they become critical, schedule preventative maintenance, and execute pre-planned response policies or mitigation strategies in an accelerated and cost-effective manner (Gunasegaram, 2024, p.461; Rosen & Pattipati, 2023, p.648).

2.4 DT interoperability as a socio-technical concept

Interoperability in DT systems is not purely a technical problem (Acharya et al., 2024,p.9). While technical literature often frames it as a connectivity or data format issue, Acharya et al. (2024) demonstrate that, interoperability failures in DT enabled CPS occur across multiple levels, extending beyond technology into how teams are organized, how responsibilities are divided, and how data meaning and context is shared across organizational boundaries. From a project management perspective, three levels are most consequential: syntactic, semantic, and organizational.

Syntactic interoperability concerns the consistency of data structures and formats across systems; semantic interoperability ensures that the meaning of exchanged data is uniformly understood; and organizational interoperability focuses on harmonizing business processes, policies, and structures across collaborating entities (Acharya et al., 2024).

When syntactic failure occurs, different engineering disciplines using different tools produce structurally incompatible outputs (Margaria & Ryan, 2023, pp.258–259) that force rework upon integration. Abanda et al.(2025,pp.817,822) further clarifies that,using different software version by stakeholders, lack of common data standard standards and interoperability makes it incredibly difficult to share project data and integrate technologies of DT supporting the argument of Margaria & Ryan.

From a project management perspective, this manifests as schedule slippage and cost overrun (Abanda et al., 2025,p.816), directly threatening the triple constraint of Projects depicted in Figure 1.10. Semantic failure compounds this further stating that, when data is structurally exchangeable but interpreted differently across teams, the DT produces outputs based on misunderstood inputs, undermining its fidelity and trustworthiness (Piroumian, 2023b,p.384). Quality objectives are compromised and stakeholder acceptance is threatened, with the cost of corrective action increasing exponentially when such failures surface late in the project lifecycle (Raydugin, 2013,pp.12,27,137).

Critically, syntactic and semantic failures do not arise randomly; they arise because teams work in organizational silos (Kinman & Tutt,2023,p.234; Rosen & Pattipati,2023,p.600) with no shared standards, no shared ownership of interfaces, and no cross-boundary governance (Abanda et al., 2025,p.822; Acharya et al.,2024,pp.6–9). As established in Figure 1.9, Grieves & Vickers (2017), further elaborated that organizational siloing and the mirroring of system architecture in organizational structure are fundamental impediments to DT integration. This argument is further supported by Moser & Grossman (2023), who recognize that a complex project is not purely a technical artifact but inherently involves the interplay among people, organizations, processes, and technology — including management, technical teams, supply chains, and end users. Consequently, applying a DT to such system means modeling the entire project ecosystem, where human behavior, mental models, and organizational dynamics both shape and constrain the information flowing between the physical and virtual environments.

Therefore, translating these socio-technical vulnerabilities into structured project-level risks is the necessary prerequisite for proactive risk monitoring and control.

2.5 Project Risk Structuring Tools for Complex Technology Projects

In complex technology projects, interoperability failures between DT components are rarely visible during parallel development phases as they remain latent within organizational boundaries until system integration forces incompatible outputs to converge, at which point their cost and schedule impact is most severe (Cooper et al.,2005,pp.30,49,66; Raydugin, 2013,p.100). Translating these socio-technical vulnerabilities into controllable project risks therefore requires a structured decomposition mechanism that maps project components, their interfaces, and their underlying organizational root causes before integration occurs. This translation is theoretically justified by the complementary integration of three established project management instruments — the WBS, DSM, and the RBS; which together bridge the gap between abstract interoperability challenges and structured, actionable project control (Gálvez et al., 2015).

The WBS systematically decomposes the total scope of the DT project into finite, manageable deliverables and discrete work packages, organized by functional discipline(Goetsch,2015,p.68;

PMI,2017,p.412). From an interoperability perspective, this hierarchical decomposition performs a critical function — it establishes unambiguous administrative ownership for each isolated component by separate technical and physical boundaries where work occurs(Bissonette, 2016,p.100), allowing project managers to assign clear accountability for deliverables at every phase of the development lifecycle (PMI,2017,pp.405,411, 426). In a multi-stakeholder DT project such as BHMS development, where electrochemists, embedded engineers, cloud architects, and suppliers develop components in parallel isolation, the WBS boundaries directly correspond to the organizational interfaces where syntactic and semantic interoperability failures will emerge — making administrative ownership inseparable from interoperability risk ownership. As demonstrate earlier in Figure 1.9, the architecture of a project's organizational structure mirrors the architecture of the technical system being built, meaning that WBS boundaries do not merely reflect administrative convenience but correspond directly to the technical interfaces where interoperability failures will emerge.

However, WBS is inherently a hierarchical tree structure (Cooper et al., 2005,p.374), it excels at defining where work happens and who owns it (Marchewka,2003,p.122), but does not explicitly model the lateral data exchanges and complex iterative interdependencies that cross these organizational boundaries (Gálvez et al.,2015,p.72)-the precise locations where syntactic and semantic interoperability failures will materialize.

To address the lateral interdependency gaps of WBS, the DSM acts as the relational bridge between technical architecture and project structure. Eppinger and Browning (2012) define the DSM as a network modeling tool used to represent the elements comprising of system and their interactions, thereby making the system's architecture explicitly visible. Because interoperability failures fundamentally occur at the interfaces where data is exchanged between disparate systems as depicted in Figure 2.7, the DSM pinpoints the complex, cross-functional

nodes where incompatible data formats or misaligned semantic interpretations will force costly rework (Acharya et al.,2024,p.2; Eppinger & Brownie, 2012, pp.132–133). Critically, the DSM identifies independent, dependent, and coupled task configurations by tracking information flow and iterative development cycles (Gálvez et al.,2015,p.73; Lin et al.,2007,p.185) ; a distinction of profound consequence required for DT projects, where coupled tasks represent bidirectional information dependencies that neither party can resolve unilaterally (Moser & Gross-

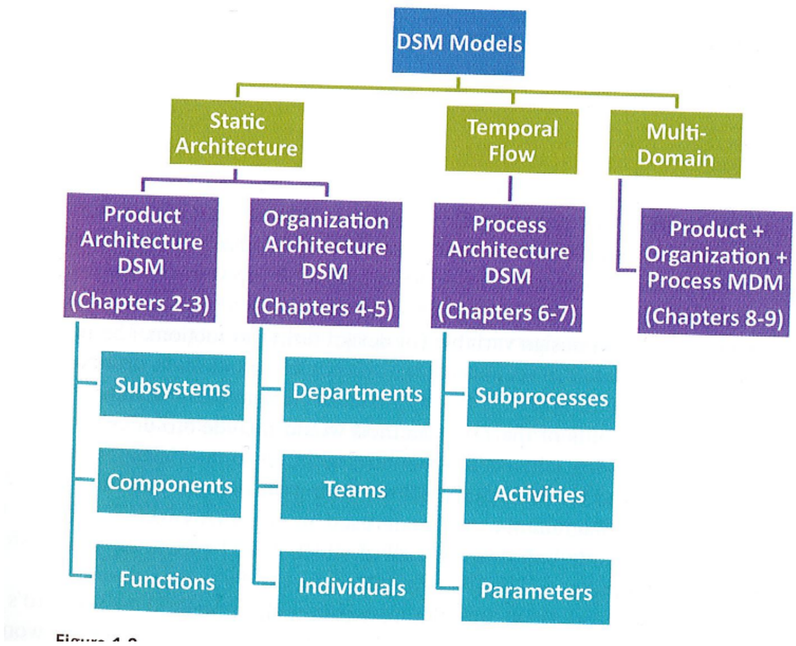

Figure 2.7. Four types of DSM Models (Eppinger & Brownie, 2012,p.11).

mann,2023). While the WBS defines components and the DSM maps their interfaces, neither framework addresses why an interface fails from a human or organizational standpoint. To address this gap, the RBS hierarchically categorizes the socio-technical root causes of project risks, extending beyond technical issues to capture vulnerabilities in leadership, communications, and organizational processes (Bissonette, 2016). Interoperability failures do not arise randomly but stem directly from these exact organizational root causes, such as teams operating in silos without shared standards (Acharya et al., 2024). Consequently, the RBS provides the formal taxonomy required to translate abstract organizational interoperability failures into identifiable and structured project risk categories (Bissonette, 2016).

The application of WBS, DSM, and RBS to DT environments requires structural adaptation, as traditional project management methods are fundamentally inadequate for the highly coupled and iterative nature of cyber-physical systems (Moser & Grossmann, 2023,p.683). Classical tools such as PERT and CPM assume linear task sequences and evaluate risks in isolation, ignoring the systemic interdependencies between project complexity and complexity-induced risks (Moser & Grossmann, 2023; Qazi et al., 2016,p.1183). Because DTs demand continuous, bidirectional data synchronization between physical and virtual entities across their entire lifecycle (Abanda et al., 2025), data interoperability risks inherently transcend individual WBS work packages and require a network-based, systemically integrated approach to risk identification and management (Qazi et al., 2016,p.1187).

Consequently, the WBS must be cross-referenced with the Process Architecture DSM to transform a static hierarchical scope breakdown into a dynamic interface matrix that explicitly visualizes the coupled tasks where syntactic and semantic interoperability must be achieved, enabling project managers to anticipate rework cycles before integration forces them to surface as depicted in Figure 2.8:

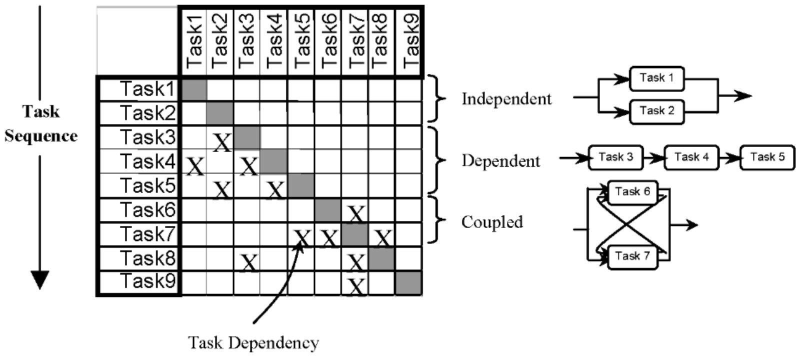

Figure 2.8. A sample Design Structure Matrix (Lin et al.,2007,p.185).

Concurrently, the RBS must be expanded beyond standard technical risk categories to explicitly incorporate the socio-technical organizational failures that allow interoperability mismatches to propagate undetected across stakeholder boundaries (Acharya et al., 2024,p.6; Bissonette, 2016,p.100). By intersecting these three adapted instruments, the project manager establishes a structured translation mechanism that converts abstract interoperability vulnerabilities into specific, assignable, and monitorable project risk events (Bissonette, 2016,pp.19,25) while a real-time monitoring instrument capable of detecting when these failures are actively occurring remains necessary, which is the conceptual role of the Project Digital Twin examined in the following section (Grieves & Vickers, 2017,p.95; Soori et al., 2023,p.2)

2.6 Toward a Pro-active Project Risk Monitoring and Control Framework In Project DT deployment in Complex Projects

In this thesis, the term Project DT as used in Research Question 2 does not refer to a digital twin of the project itself, but to a DT-enhanced Project Management Information System (PMIS) that is, a project risk management architecture whose monitoring and control functions are informed by data generated within the project's engineering-level DT ecosystem.Data interoperability challenges have been identified in the literature as a significant impediment to successful DT implementation in complex projects (Acharya et al., 2024), yet existing project risk management frameworks do not account for these challenges as a distinct, anticipitable category of project risk that can be systematically identified, monitored, and acted upon before they propagate into project-level consequences.

To address this gap, the thesis develops a conceptual DT-enhanced PMIS comprising WBS for scope decomposition and risk ownership identification, process DSM for dependency mapping and impact tracing, and RBS for risk categorisation according to the some of six interoperability levels that will be identified in the case study project inspired from the literature review. This PMIS is designed to detect interoperability failures as they manifest through observable project-level symptoms such as integration test failures, deliverable rejections, or output divergences between coupled DT subsystems and to trace, classify, and respond to those failures before they propagate into schedule delays, cost overruns, or design rework that also aligns with the modern project risk management strategy.

- **Gap in the current study:** In traditional project risk management, monitoring is heavily based on periodic performance reviews, status reports, and manual checks (Bissonette,2016 ,pp.58-60). The problem with this approach in a highly integrated project like a BHMS is that technical interoperability failures such as data format mismatches or communication protocol errors propagate instantly. By the time a project manager reads a periodic status report, the interoperability failure has already caused system downtime or rework. Good risk control relies on identifying early warning signs as fast as possible to initiate remedial actions and lower the cost of change.

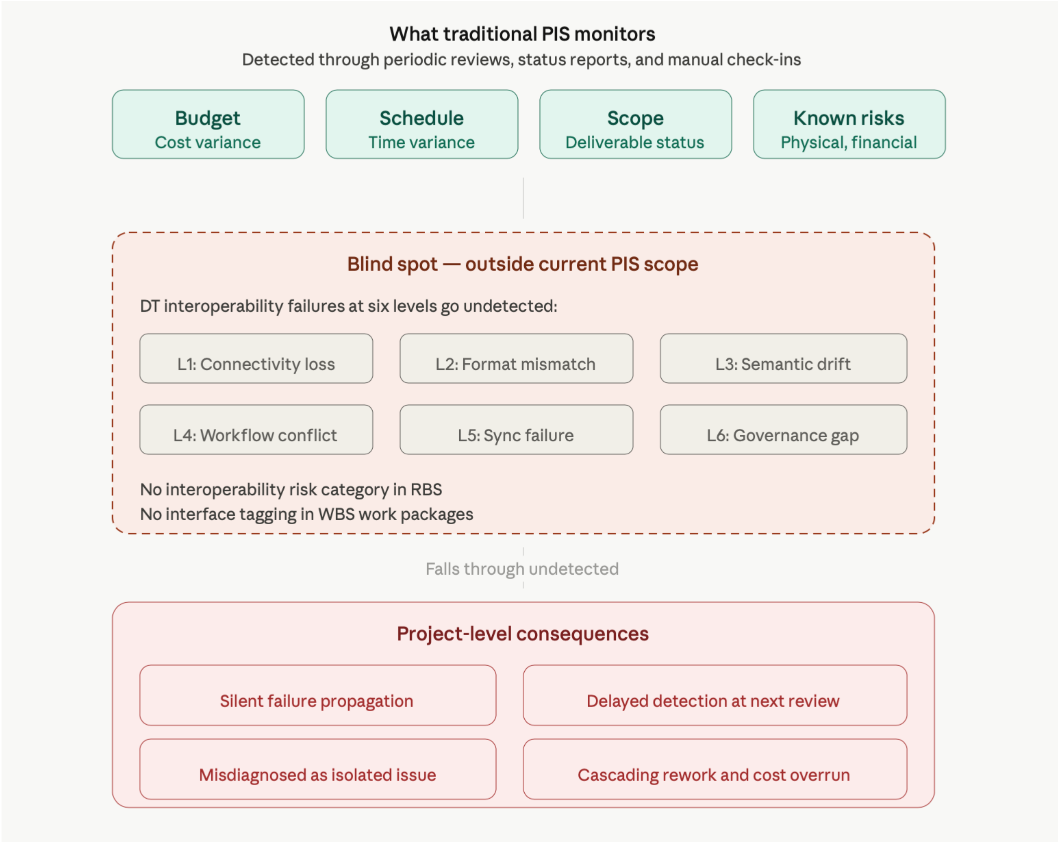

Figure 2.9. Current Gap Identified in PIS (Image generated through prompt in claude AI).

Acharya et al. (2024) identified 77 interoperability challenges across six levels. But current literature doesn't tell how a project manager will decide to control those risks during project execution, where in the project structure they will cause damage, who is responsible for resolving them, or how to respond. Their framework is a diagnostic taxonomy. It is not a management instrument.

The proposed framework operates across three sequential phases that correspond to the project lifecycle: pre-deployment risk structuring, execution-phase monitoring, and response activation. Each phase builds upon the outputs of the preceding one, and together they constitute a continuous risk monitoring and control mechanism that is embedded within the project's existing information architecture.

Phase 1: Pre-deployment Interoperability Risk Structuring: The first phase takes place during project planning, before any digital twin subsystem is deployed or integrated (PMI,2017,p.405). Its purpose is to pre-structure the project's information system so that interoperability risks are anticipatable rather than discoverable only after they have caused damage (Bissonette, 2016,p.80). The project manager begins by conducting a systematic screening of the Work Breakdown Structure (WBS) against the six-level interoperability taxonomy proposed by Acharya et al. (2024). Every work package that involves a data exchange; whether between two or more DT subsystems, between a DT and a physical asset, or between platforms provided by different vendors will be flagged as an interoperability-exposed work package. For each flagged work package, the project manager then identifies which interoperability levels constitute relevant risk exposures. To illustrate, a work package involving data handoff between an electrochemical DT developed by Vendor A and a thermal management DT developed by Vendor B would be assessed for technical risk (whether their communication protocols are compatible), syntactic risk (whether their data formats can be correctly parsed by the receiving system), semantic risk (whether shared variables such as state-of-charge are defined using the same measurement conventions), and organisational risk (whether the two vendors maintain aligned governance and change management processes). These identified exposures are then registered within the Risk Breakdown Structure (RBS) as specific, anticipatory risk entries (Bissonette,2016,pp.47,72). Critically, these entries are not recorded in generic terms such as "technical risk" but in precise, interface-specific formulations for example, "semantic inconsistency risk at the electrochemical-thermal DT interface due to differing state-of-charge reference conventions." This level of specificity is essential because it determines the diagnostic accuracy and response relevance of the subsequent phases. Finally, the Design Structure Matrix (DSM) is used to map the dependency pathways associated with each flagged interface. For each interoperability-exposed work package, the DSM identifies which downstream tasks depend on the data output of that interface, thereby establishing in advance the propagation pathway that a failure at that interface would follow through the project plan. The output of Phase 1 is a project information system that has been pre-configured to recognise interoperability risk: a WBS with tagged interfaces, an RBS with level-specific anticipatory risk entries, and a DSM with mapped impact pathways. This pre-structuring ensures that when interoperability failures manifest during execution, the project team is not starting from a position of ignorance.

Phase 2: Execution-Phase Monitoring through Project-Level Indicators:

The second phase operates during project execution and is concerned with the continuous detection of interoperability failures as they surface through observable project-level symptoms. It is important to emphasise what the project manager monitors in this phase and what falls outside this scope. The project manager does not monitor the DT's internal data streams directly; that responsibility belongs to the engineering team. What the project manager monitors are the project-level consequences of interoperability failures — consequences that are observable through standard project management instruments. Five categories of project-level indicators serve as the primary monitoring signals. First, integration test pass and fail rates at tagged interfaces provide direct evidence of technical or syntactic failures. Second, deliverable rejection rates at interoperability-exposed work packages indicate that outputs from one DT subsystem are not meeting the acceptance criteria of the receiving subsystem. Third, the frequency of interface specification change requests between vendor teams signals emerging pragmatic or organisational misalignments. Fourth, schedule variance in work packages downstream of flagged data exchange points suggests that an upstream interoperability failure is silently propagating through the dependency chain mapped in the DSM. Fifth, the number of unresolved data interpretation disputes escalated during design reviews provides evidence of semantic inconsistencies between domain-specific DT models. Each of these indicators is linked back to specific interoperability levels through the RBS structure established in Phase 1. A rising integration test failure rate at a specific interface points toward a Level 1 technical or Level 2 syntactic problem. A pattern of deliverable rejections in which two subsystem outputs diverge despite both passing their individual validation tests suggests a Level 3 semantic problem — the data is structurally correct but means something different to each system. A surge in interface change requests between two vendor teams suggests a Level 4 pragmatic or Level 6 organisational problem. The framework thereby translates engineering-level interoperability failures into the language of project management — schedule variance, rework frequency, and milestone risk — without requiring the project manager to possess specialised data engineering expertise.

Phase 3: Response Activation through RBS Classification The third phase is activated when a monitoring indicator from Phase 2 exceeds a pre-defined threshold, signalling that an interoperability failure has manifested and requires a management response.

The distinguishing feature of this phase is that the response pathway is not generic; it is determined by the RBS classification of the failure's root cause. In a conventional risk management process, a failed integration test would typically be classified under a broad category such as "technical risk," and the project manager would assign an engineer to investigate and resolve the issue on an ad hoc basis. The proposed framework replaces this generic approach with a structured, level-specific response logic. A Level 1 technical failure such as a connectivity loss or protocol rejection at a DT interface triggers an infrastructure review and protocol compatibility audit. Level 2 syntactic failure such as a data format mismatch causing silent misparsing triggers middleware reconfiguration or data format adapter deployment. A Level 3 semantic failure such as two DT subsystems interpreting the same transmitted value using different measurement conventions triggers an ontological alignment session between the two domain teams, because the problem is not a code defect but a definitional inconsistency that cannot be resolved through debugging alone. A Level 4 pragmatic failure triggers a workflow redesign to ensure that the two systems are using shared data in operationally compatible ways. A Level 5 dynamic failure triggers an architecture review of the real-time synchronisation mechanisms governing inter-DT data exchange. A Level 6 organisational failure triggers escalation to senior management for governance realignment between collaborating entities. The operational value of this level-specific response logic lies in its diagnostic precision. It prevents the project manager from expending weeks on code-level debugging when the actual root cause is a semantic convention mismatch between two domain models, or from convening technical workshops when the actual problem is a governance misalignment between two vendor organisations that can only be resolved through contractual or managerial intervention. By connecting the detected symptom (Phase 2) to a classified root cause (Phase 3) through the pre-structured RBS (Phase 1), the framework ensures that each interoperability failure is met with the response category most likely to resolve it, thereby reducing diagnostic delay, minimising misdirected corrective effort, and containing the downstream impact on project schedule and cost.

Table 2.3. Three Theoretical Approaches to Project Risk Management (Adapted from Bisonette, 2016;Cooper ,2005;Marchewka,2003; Pmbok,2017;Raydugin,2013).

Theoretical Approach	Author / Source	Key Contribution / Statement	Key Concepts / Attributes
A Defined and Adaptive Process (The "How")	PMBOK® Guide (PMI)	Defines seven processes: Plan, Identify, Perform Qualitative/Quantitative Analysis, Plan Responses, Implement, Monitor. Detailed inputs, tools, outputs.	Structured process, repeatability
	Cooper (Project Risk Management Guidelines)	Step-by-step guide; Chapter 25 is a process checklist. Steps: context, identify, analyze, evaluate, treat, monitor, review.	Sequential steps, methodology
	Bisonette (Case Studies)	Evaluates tools (EVMS, IMS) within a process. Second project failure attributed to wrong process ("predictive" vs "iterative").	Process selection, methodological failure
	Raydugin (Project Risk Management)	Builds system on formal process (Figure 2.2). Three pillars: framework, process, tools. Emphasizes process over tools.	Formal process, system pillars, process priority
A Sophisticated Analytical Toolkit (The "What")	Raydugin (Nature of Project Uncertainties)	Deconstructs risk into: general uncertainty (aleatory – inherent variability), uncertain events (epistemic – discrete events), unknown unknowns.	Risk decomposition, aleatory vs epistemic, unknown unknowns
	Raydugin (Adequacy of Methods)	Method must match object. Critiques deterministic qualitative methods (e.g., simple matrices) for cost/schedule; requires probabilistic quantitative methods (Monte Carlo).	Method alignment, qualitative vs quantitative, Monte Carlo
	Goestsch (Project Planning: Risk Plan)	Introduces quantitative tools: distribution curves (Normal, Triangular, Beta), decision trees. Applies to time and cost.	Quantitative tools, distribution curves, decision trees
A Deep Understanding of Human and Organizational Context (The "Who" and "Why")	Jack (Nature of IT Projects)	CHAOS report cites user involvement, executive support, clear requirements as top success factors. Failures stem from human/organizational causes.	Software crisis, success factors, human causes
	Jack (Managing Project Risk)	Frames risk with stakeholders, legal, processes, environment, technology, organization. IT Risk Framework with MOV at core.	Risk framework, stakeholder analysis, MOV
	Bisonette (Case Studies)	Compares projects across organizational influences (funding), competitive landscapes (sole-sourced vs open market), priorities (contractual vs time-to-market).	Organizational context, competition, priority trade-offs
	Bisonette (Causes of Unsuccessful Project Execution)	Fishbone diagram (Fig. 5.2) splits causes into team-influenced (plans, controls, leadership) and organizational/external factors (processes, resources).	Root causes, team vs external factors, causal model
	Raydugin (Risk Management Governance)	Introduces "line of sight" and three dimensions (vertical, horizontal, in-depth). Highlights role of bias (psychological, organizational) as key risk factor.	Governance, line of sight, bias as risk

Chapter 3

Methodology

This chapter explains how the research was designed, executed, and validated. It begins by outlining the qualitative research approach adopted for this study, which combines a literature-driven conceptual case study with a socio-technical analytical lens to investigate data interoperability risks in Digital Twin-enabled Battery Health Management System (BHMS) projects. The next section introduces the case context — an EV BHMS multi-physics model development scenario constructed from published industrial and scholarly sources — and justifies the selection of the BHMS development project as the unit of analysis, understood as a socio-technical system in which data interoperability challenges across its multi-stakeholder, multi-domain architecture translate into project-level risks. This is followed by a focused account of how data was collected through a structured literature search across multiple scholarly databases and an industry whitepaper obtained through a professional contact within the Business Finland metaverse ecosystem, with attention to search strategy, selection criteria, and the scope of the final paper set. To ensure methodological transparency, the chapter also discusses how trustworthiness was established through source triangulation across technical and managerial literature domains, documented analytical logic using standard project management instruments (WBS, DSM, RBS), and traceable reasoning chains linking identified interoperability challenges to project-level risk categories. Finally, ethical compliance and the limited role of AI-assisted tools in the research process are briefly outlined. Together, these elements provide the methodological foundation for the case analysis and results presented in the subsequent chapters.

3.1 Research Approach & Framework

Researchers employ different research approaches based on the nature of study that offers flexibility of collecting and interpreting data in different ways. The three most commonly used research approaches include quantitative, qualitative, and mixed methods (Taherdoost,2022).

This thesis investigates how data interoperability challenges in Digital Twin-enabled Battery Health Management System (BHMS) projects can be identified as project-level risks, and how a DT enhanced PMIS can support their monitoring and control. The objective is not only to analyze a specific case but also to develop a transferable risk management framework that aligns with how complex, technology driven projects operate in practice. The study combines case based inquiry with design science principles to produce both theoretical insight and practical utility. It follows a structured process that moves from interdisciplinary literature synthesis toward a redesigned risk monitoring and control model grounded in documented industrial conditions.

Preliminary research from literature reviews and industrial whitepaper suggested that DT exchanges information from physical to digital asset and hence real time information sharing is the core essence of successful functionality of a twin system. It began with a question: If data interoperability failures in DT deployments cause technical problems, can they be also translated into project-level risks since this was not explored pre-dominantly in the Project management perspective domain? The literature review revealed that interoperability is not simply a technical connectivity issue — it is a socio-technical boundary failure that operates simultaneously across syntactic, semantic, and organizational levels (Acharya et al., 2024). This reframing shaped every design choice that followed. Holmström et al. (2009, pp.10-11) describe abductive reasoning as the ability to connect different knowledge domains and see commonalities between them, a form of reasoning fundamentally distinct from induction and deduction. In design science, this abductive process drives the incubation of novel solutions by combining insights from parallel domains (Holmström et al., 2009, p.11). In this thesis, those parallel domains were project management, systems engineering, information systems, and socio-technical theory. No single domain could frame the problem correctly on its own. The solution emerged from their intersection.

Tobi and Kampen (2018, p.1212) built their Methodology for Interdisciplinary Research (MIR) framework on exactly this principle where the research question leads for all decisions in the various stages of research. The MIR framework refuses the idea that any scientific tradition has exclusive ownership of any methodological approach (Tobi & Kampen, 2018, p.1217) as depicted in Figure 3.1:

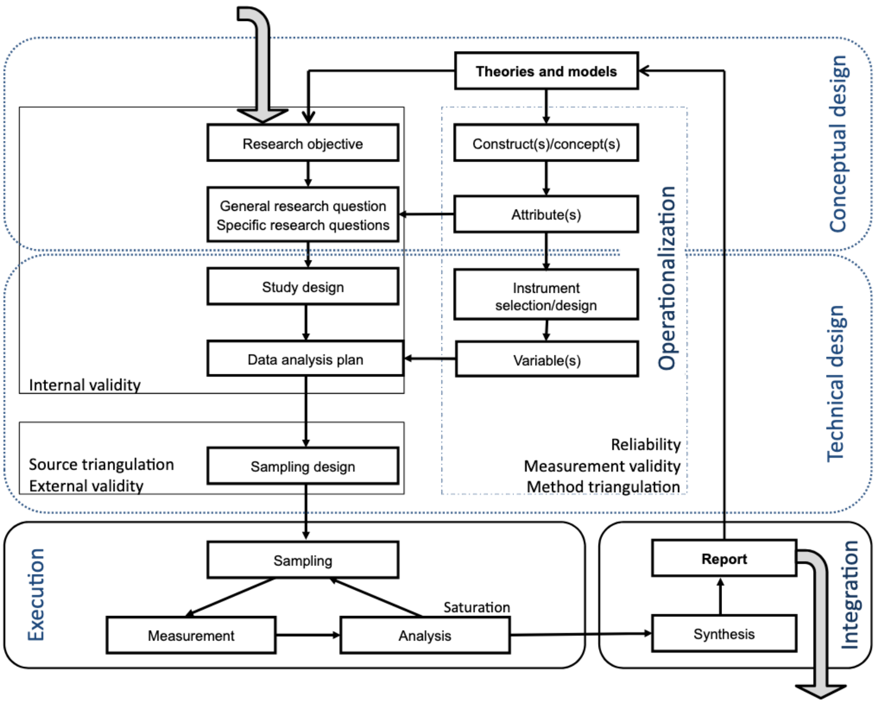

Figure 3.1. The Methodology of Interdisciplinary Research framework (Tobi & Kampen,2018,p.1212).

The problem this thesis addresses — managing interoperability risks in DT enabled BHMS projects that is simultaneously a technical engineering challenge and an organizational management challenge. Approaching it through a positivist lens alone would reduce it to measurable variables while ignoring the organizational dynamics that, as Chapter 2 established, are structurally inseparable from the technical risk landscape (Moser & Grossmann, 2023, pp.677–681). This thesis follows a pragmatic research orientation as documented by Helo et al. (2019) where case study and design science approaches were identified as inherently pragmatic. Additionally, these authors elaborated that, design science that is also referred to as constructive research which provides immediate value by proposing a technical solution. This pragmatic orientation is further supported by Holmström et al. (2009, pp.6,33), who explicitly classify the knowledge interest of design science research as pragmatic, where the researcher's commitment is to solving the problem rather than to conduct purely theoretical explanation.

3.2 Case Study & Unit of Analysis

The case analyzed in this thesis is the development of a Digital Twin enabled Battery Health Management System (BHMS) for an Electric Vehicle (EV) platform operating within the smart manufacturing paradigm. In this development scenario, multiple engineering disciplines such as electrochemistry, embedded systems, and cloud architecture reasearch groups work in parallel to deliver a unified system capable of predicting State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL) of lithium-ion battery packs. The system requires a "Hybrid Twin" approach, combining physics based models developed by electrochemists with data-driven AI/ML models developed by cloud architects, deployed across two fundamentally different computing environments: the edge (the vehicle's onboard BMS with millisecond response requirements and limited processing power) and the cloud (with scalable computing capacity but communication latency constraints). This coordination setting differs from conventional single-platform DT deployments, making it a strong test case for the DT-enhanced PMIS framework developed in Section 2.5. This case was not selected for representativeness but because it exposes the interoperability challenge in its most acute form.

The EV BHMS case concentrates every critical feature of the research problem in a single bounded context, one namely heterogeneous DT models developed by different stakeholder groups using incompatible tools (MATLAB, COMSOL, Python/PyBaMM) followed by vendors protecting intellectual property through "black box" models. Real-time synchronization requirements where data compression introduces quality degradation and safety critical outputs where interoperability failure carries direct liability consequences. The case is constructed from multiple published sources peer-reviewed studies (Zhang et al., 2024; Naseri et al., 2023; Ibrahim et al., 2023; Issa et al., 2023), an industrial whitepaper (Case organization X), and authoritative handbook chapters (Crespi et al., 2023; Acharya et al., 2024; Margaria & Ryan, 2023) — ensuring verifiable and triangulated evidence.

This thesis defines its unit of analysis as the BHMS development project itself — specifically, the coordination boundaries where different engineering disciplines must exchange data, align interpretations, and reconcile governance structures for the project to succeed. These boundaries were not observed in a live project environment but were systematically identified through the reviewed literature using the six-level interoperability taxonomy proposed by Acharya et al. (2024) and the socio-technical framing established in Section 2.3 as depicted below in Figure 3.2:

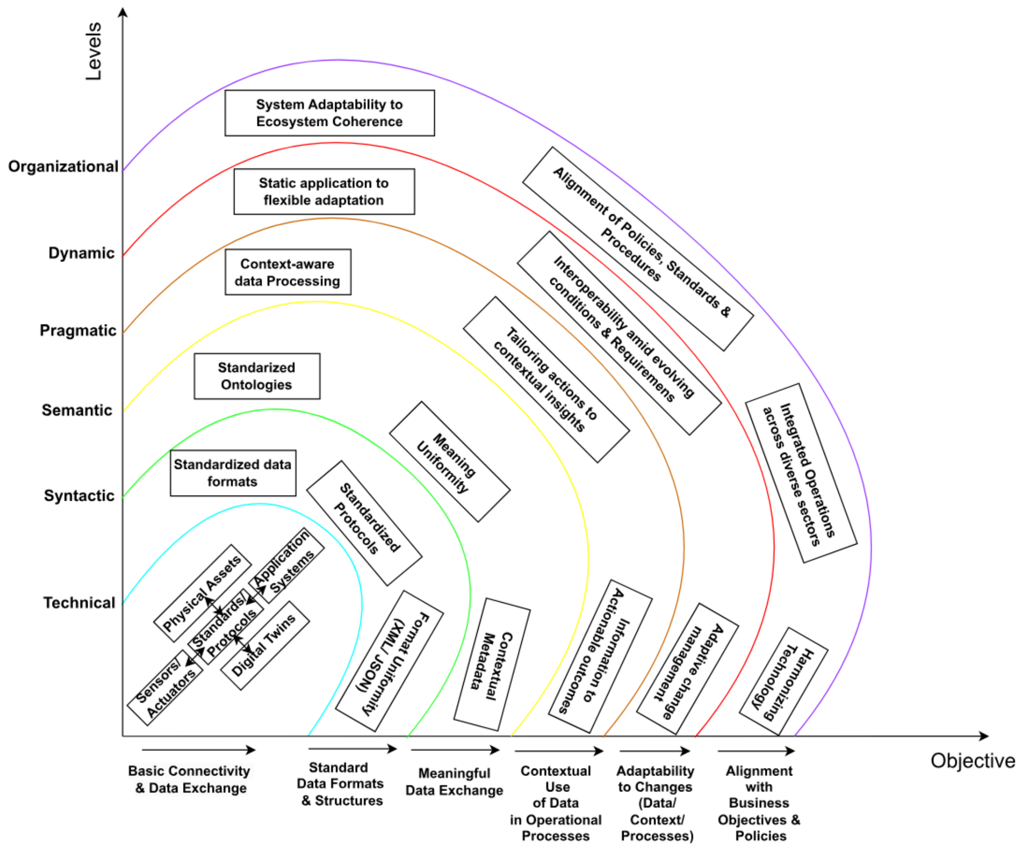

Figure 3.2. A Hierarchical Presentation of the Six Levels of Interoperability for DT-CPS (Acharya et al.,2024,p.6).

The analytical procedure that makes this study replicable is as followed: the BHMS development process was decomposed into work packages using WBS, the data exchange dependencies between those work packages were mapped using DSM, and the interoperability risk exposures at each dependency were classified by level (syntactic, semantic, organizational) using RBS.

3.2.1 Qualitative approach & justification of Innovative Research Methodology based Case Design

A qualitative research approach was adopted. The justification operates at two levels.The nature of the research questions and the practical constraints of the study makes it an entirely conceptual driven thesis backed by multiple literature review.

The research questions formulated in Table 1.1 are exploratory and constructive. RQ1 asks how interoperability challenges can be identified and translated into project-level risks. RQ2 asks how a Project Digital Twin can support the monitoring and control of those risks. Neither of the questions seek to test a hypothesis or measure prevalence. Both require the researcher to synthesize knowledge from multiple domains, identify conceptual relationships, construct new analytical instruments, and propose a framework. These are fundamentally qualitative activities.

This is consistent with the design science orientation. Holmström et al. (2009, p.6) make a critical distinction stating that in explanatory research, the phenomenon already exists and the researcher seeks to understand it through the lens of design science. The artifact must be created before it can be evaluated. The creation of the DT-enhanced PMIS framework hence proposes the three-phase risk monitoring and control mechanism developed in Section 2.5 follows an inherently constructive process. It cannot be reduced to quantitative measurement because the object of study did not exist prior to the research.

An important constraint also shaped the approach. The study initially considered conducting semi-structured interviews with project managers, systems engineers, and DT practitioners in the EV manufacturing sector. However, due to the highly specialized and commercially sensitive nature of DT deployment in EV battery development, gaining access to industry informants proved infeasible within the timeframe and scope of a master's thesis. This is a real limitation.

The constraint redirected the methodology toward a literature-driven conceptual case study; an approach that well-supported in the methodological literature. Lê and Schmid (2022,p.312) demonstrate through their review of exemplar studies that scholars can innovate in data generation by relying on unconventional sources, including published case documentation and organizational archives, rather than traditional interviews. Their exemplar studies show that such innovation can produce contributions of the highest quality when combined with rigorous analytical frameworks as depicted in Figure 3.3:

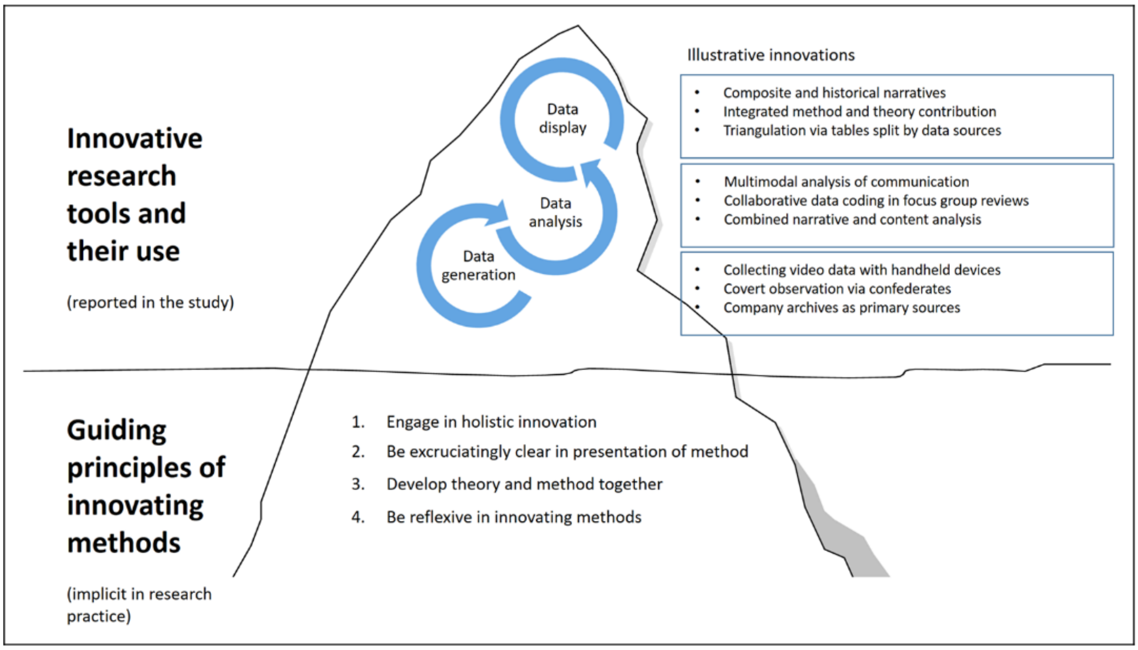

Figure 3.3. Innovating research methods as two-layered process ("innovation iceberg") (Lê & Schmid,2022,p.327).

The design science tradition reinforces this further. Holmström et al. (2009, p.15) emphasize that the design scientist's commitment is to solving the problem, not to any particular data collection method. In the solution incubation phase, the researcher constructs the problem through scanning of parallel knowledge domains and abductive cross-disciplinary reasoning (Holmström et al., 2009, p.11) — activities that rely on published literature and documented evidence rather than on primary interviews. The case study in Chapter 4 is therefore constructed from peer-reviewed studies, industrial whitepapers (including the Case company X report on digital twin implementation issues), and authoritative handbook chapters that document interoperability challenges with sufficient detail to permit structured analysis. The evidence base is verifiable, triangulated across multiple independent sources, and not dependent on the subjective recall of individual informants.

3.3 Data Collection

This section outlines the data sources used to investigate data interoperability risks in DT-enabled BHMS projects and their translation into project-level risk categories. Since this thesis is a literature-driven conceptual study, the primary data source is a structured literature review supplemented by an industry whitepaper. Together, these sources provided the empirical base for identifying interoperability challenges, constructing the case context, and developing the DT-enhanced PMIS framework. The initial research direction was established through an industry whitepaper published by Company X, obtained via email communication with a professional contact connected to the metaverse industry; initiative of Business Finland who provided me this whitepaper from Company X whose operation is based in Sweden and it is a multinational corporation. Company X specializes in measurement tools and particularly provides solutions for metrology, reality capture, and positioning technologies in terms of geospatial data tools and software. Their major offerings feature AI-driven solutions, digital twins, robotics, and automation technologies.Company X contacted around 660 C-suit (CEO,CFO,COO) executives and senior leaders across 11 industries while conducting the Digital twin survey, and their aim was to uncover the innovative ways organizations are using digital twins and the connection between technological maturity and organizational success. Industries ranged from Automotive, Construction, Manufacturing to Aerospace and Oil and gas industries to name a few. So, when I was searching for one specific question regarding what is one of the obstacles to the application of the digital twin in industry, I got my answer from this survey report depicted in Figure 3.4:

This whitepaper documented practical challenges organizations face during digital twin implementation and identified data quality and interoperability as the most significant barrier. The document served as the problem anchor for the study, narrowing the research focus from digital twin adoption broadly to data interoperability specifically and its consequences for project-level risk management. Building on this foundation, a structured literature search was con-

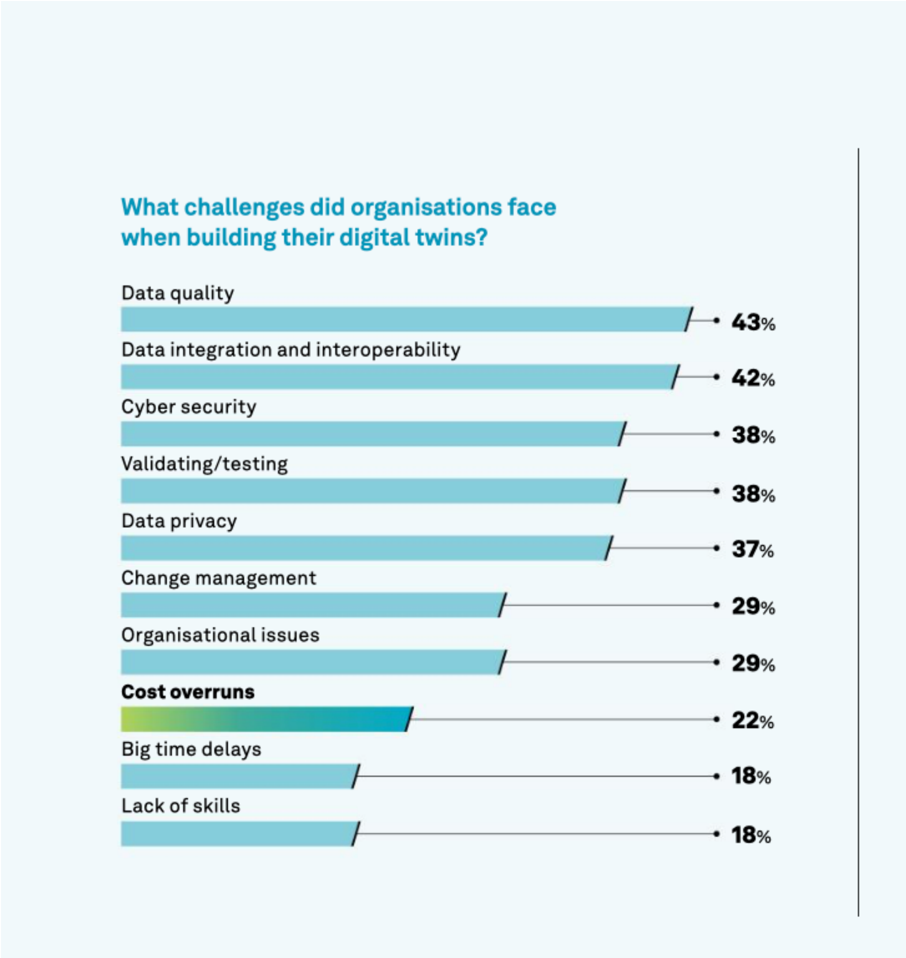

Figure 3.4. Challenges faced during digital twin implementation: Collected data from the report of Company X.

ducted across multiple scholarly databases: Google Scholar, Scopus, IEEE Xplore, ScienceDirect, arXiv, and ResearchGate. The search was executed in two phases corresponding to the two domains the thesis connects. In the first phase, search strings targeting the technical domain were used to identify case-relevant literature on EV battery digital twin development. These strings included “Digital twin in smart manufacturing industry,” “EV BHMS digital twin project”. In the second phase, search strings targeting the project management domain were used to identify literature on risk management in complex interdisciplinary projects. These strings included “Complex projects,” “Digital twin and project management,“Project risk management,” “Digital twin and risk assessment,” and “DSM and project scheduling.” The two-phase approach was deliberate: the first phase established what interoperability failures look like in a concrete technical context, while the second phase established how such failures can be structured, monitored, and controlled using project management instruments. The initial search yielded more than 137 documents including books and paper from different scholarly websites, from there 14 papers were relevant to Battery Digital twin based in EV BHMS system, finally selected. These were screened for relevance based on three criteria: the paper must address digital twin implementation in a multi-stakeholder or multi-domain engineering context, the paper must document or discuss data interoperability challenges at the system integration level, and the paper must contribute either technical case evidence or project management analytical tools applicable to the BHMS context. After screening, 11 papers were found from web for specific case review of EV BHMS projects. One exclusive paper from University of Oulu, Finland that covered the interoperability challenges during digital twin implementation provided me advanced research direction towards data interoperability issues. The excluded papers either addressed digital twin applications without discussing interoperability, focused on single-domain implementations without cross-boundary coordination challenges, or lacked sufficient methodological detail to support analytical application. In addition to the 11 selected papers and the Company X whitepaper, the literature review relied on established project management references including PMBOK (2017), Specific Project risk management books such as Bissonette (2016), Cooper et al. (2005), Raydugin (2013), Marchewka (2003), and Goetsch (2015) — to ground the risk management instruments (WBS, DSM, RBS) and the socio-technical framing within recognized theoretical foundations. The DT related framework, functionality of DT related to data interoperability issues were retrieved from 4 books ment domain. No primary empirical data (interviews, surveys, or system records) was collected for this study. The research relies entirely on secondary data from published, peer-reviewed, and industry sources. This is a deliberate methodological choice: it ensures that every data point is verifiable and independently accessible by another researcher, which satisfies the replicability requirement emphasized in the University of Vaasa thesis guideline. The limitation of this approach — the absence of proprietary organizational data or practitioner validation — is acknowledged in Section 1.5 and revisited in the conclusions. Together, these sources provided the evidence base for identifying where interoperability failures originate in a multi-physics BHMS development project, how those failures manifest as project-level risks, and how a structured PMIS framework can translate them into anticipatable, detectable, and actionable risk categories using standard project management instruments. A detailed picture of this thesis research and data collection methodology has been portrayed in Figure 3.5:

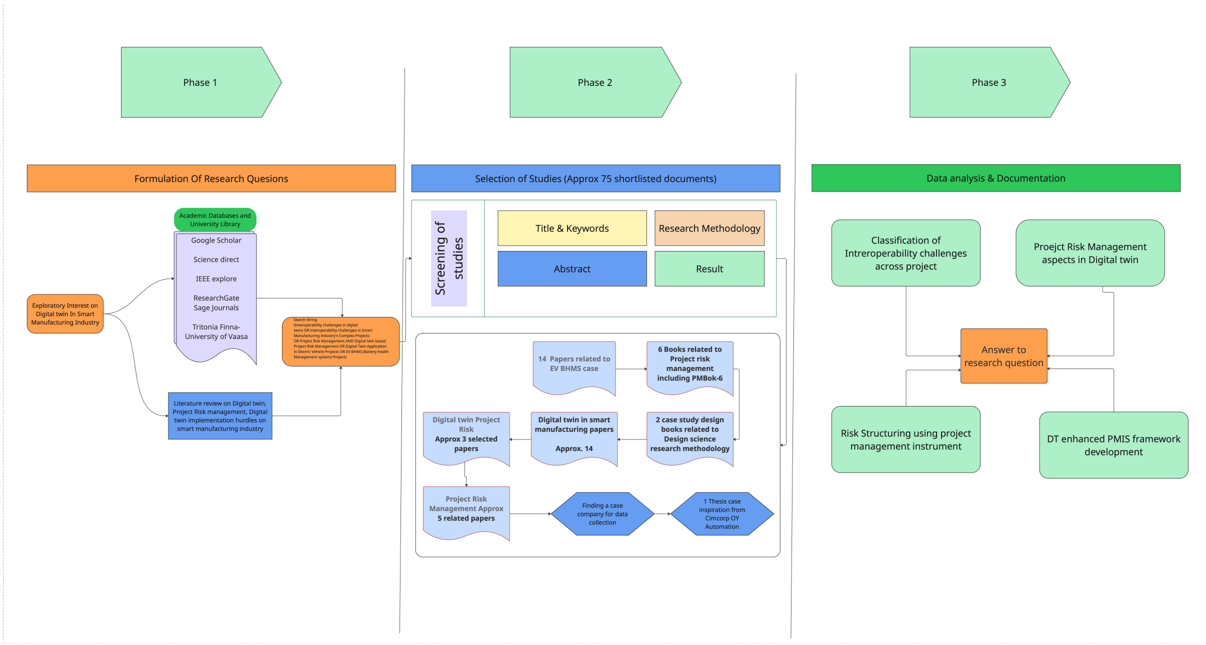

Figure 3.5. Research Methodology & Data Collection process summary.

3.4 Trustworthiness, validity & ethical use of AI

This section addresses how the trustworthiness of the research was established. While the study follows a design science orientation grounded in a literature-driven case study, care was taken to ensure that its insights rest on methodological clarity and procedural traceability. Yin (2018, p.42) identifies four tests commonly used to judge the quality of research designs in case study research: construct validity, internal validity, external validity, and reliability. Each is addressed below in relation to the specific conditions of this thesis.

3.4.1 Construct Validity

Construct validity concerns whether the study correctly operationalizes the concepts it claims to study (Yin, 2018, p.42). In case study research, a common criticism is that researchers rely on subjective judgments rather than sufficiently operational measures (Yin, 2018, p.43). This thesis addresses this risk in two ways. First, the core construct — data interoperability risk — was not defined loosely or left to the researcher's interpretation. It was operationalized through Acharya et al.'s (2024) six-level taxonomy, which provides externally validated, precisely defined categories: connectivity loss, format mismatch, semantic drift, workflow conflict, synchronization failure, and governance gap. Each risk identified in the case study is classified against these predefined levels, ensuring that the analysis is anchored to a documented conceptual framework rather than to the researcher's impressions. Second, Yin (2018, p.43) recommends the use of multiple sources of evidence as a tactic for strengthening construct validity, with data needing to converge in a triangulating fashion. The case study was constructed from peer-reviewed journal articles, industrial whitepapers, and authoritative handbook chapters — independent sources that document the same interoperability challenges from different vantage points. No single source determined the analysis. The convergence across these sources ensures that the interoperability risks identified are not artifacts of any individual study.

3.4.2 Internal Validity

Internal validity is primarily a concern for explanatory case studies that seek to establish causal relationships (Yin, 2018, p.45). Yin explicitly notes that this test is not applicable to descriptive or exploratory studies. This thesis is exploratory and constructive — it does not claim that interoperability failure x causes project outcome y in a deterministic, experimentally controlled sense. Rather, it proposes a structured causal logic: interoperability failures at specific DT interfaces (identified through the WBS) propagate through coupled task dependencies (mapped through the DSM) and produce project-level consequences in schedule, cost, and quality (classified through the RBS). Each link in this chain is supported by multiple independent literature sources rather than by the researcher's inference alone. The structured decomposition through the three instruments — where every risk can be traced from its interface location through its propagation pathway to its project-level consequence — provides the kind of explanation-building logic that Yin (2018, p.46) identifies as one of the key tactics for addressing internal validity, even in studies that are not purely causal.

3.4.3 External Validity

External validity concerns whether and how a study's findings can be generalized beyond the immediate case (Yin, 2018, p.46). Yin (2018, p.37) is emphatic that statistical generalization —

extrapolating from a sample to a population — constitutes a fundamental misapplication when imposed upon case study research. Case studies do not generalize to populations; they generalize to theoretical propositions. Yin (2018, p.38) terms this analytic generalization, whereby the case study sheds empirical light on theoretical concepts or principles, producing lessons learned that can be applied to reinterpreting existing studies or defining new research in other concrete situations. This thesis pursues analytic generalization. The three-phase risk monitoring and control framework is not claimed to apply to all DT projects universally. It is proposed as a transferable framework whose logic — first create visibility into interoperability risks through structured decomposition, then support better project decisions through level-specific response classification — can be adapted to other complex DT deployments in smart manufacturing. The framework's modularity supports this: its components (WBS tagging, DSM mapping, RBS classification, three-phase monitoring) can be applied independently or in combination depending on the project context. However, this transferability has not been empirically tested beyond the conceptual case, and doing so remains a direction for future research.

3.4.4 Reliability

Reliability concerns whether another researcher, following the same procedures, could arrive at the same findings and conclusions (Yin, 2018, p.46). Yin (2018, p.47) recommends that the researcher document procedures explicitly, conducting the research who must be able to reproduce the same results. In this thesis, reliability is supported by several design choices. The empirical base consists entirely of published, verifiable sources any researcher can access the same journal articles, handbook chapters, and whitepapers. The framework development process is documented through explicit steps such as gap identification (Figure 2.10), tool selection and adaptation, integration architecture, and operationalization through the three-phase mechanism (Section 2.5). The analytical framework itself — the composite WBS–DSM–RBS instrument provides a structured and transparent procedure: each work package is screened against predefined interoperability levels, each dependency is mapped in the DSM, and each risk is classified in the RBS according to established categories. This procedural transparency constitutes the audit trail that Yin (2018, p.47) identifies as essential for reliability in case study research.

3.4.5 Awareness of Limitations

This thesis acknowledges its limitations explicitly. The framework is conceptual and has not been validated in a live project environment due to the nature of Project because organizations are still experimenting with many projects and hence organizations specifically working with such digital twin implementation projects working in team were challenging in terms of conducting interview sessions, as per the instruction the sample size of interview is also a factor when it comes to questionnaire validity, hence it was already out of scope after careful guidance from the supervisor. The literature driven case, while triangulated and verifiable, does not capture the tacit knowledge, informal communication, and real-time decision dynamics that primary data collection would have revealed, hence it is the limitation. The study does not evaluate organizational culture or factory operations in detail. These limitations define the boundary between Phases 1–3 of design science, which this thesis covers, and Phase 4 was left for formal empirical testing which remains for future research (Holmström et al., 2009, p.17). The research design was structured to allow this future step: the framework's modular components, documented procedures, and predefined analytical categories mean that a subsequent researcher could apply the same instrument to a live BHMS project and compare the results against the conceptual case presented here.

3.4.6 Ethical Use of AI

AI-assisted tools were used in a limited and transparent capacity during the research process. Specifically, AI language models (such as ChatGPT and Claude) were employed as supplementary aids for academic formatted language refinement, structural feedback on draft sections. In some instances, photos were developed using claude AI. At no point did AI tools generate the analytical content, theoretical arguments, risk classifications, or framework design presented in this thesis. All literature searches, source selection, conceptual reasoning, framework development, and analytical conclusions are the sole intellectual work. AI-generated outputs were always reviewed, verified against original sources, and rewritten before inclusion. In accordance with the University of Vaasa thesis guidelines (Helo et al., 2019), all sources cited in this thesis were read, evaluated, and interpreted in thesis independently.

Chapter 4

Case Study

The global transition toward sustainable mobility, driven by essential policy targets and environmental mandates, positions Electric Vehicle (EV) battery technology as a central component of contemporary transportation and energy systems (Naseri et al., 2023, pp.1-2; Verma et al., 2024; p.815). Lithium-ion batteries, the dominant energy storage solution, are complex electrochemical systems facing inherent challenges related to safety (such as thermal runaway), durability, complexity (non-linearity and coupling), and longevity (Anandavel et al., 2021, p.356; Issa et al., 2023, pp. 1-5; Wang et al., 2021, p.2).

To maximize performance, extend operational life, and ensure safety, EV manufacturers are rapidly adopting digital solutions under the umbrella of IR4 and Smart Manufacturing. This environment necessitates continuous integration and adaptive management, shifting the industrial paradigm from standardized mass production toward flexible mass customization in a highly interconnected ecosystem (Lazaro et al., 2018,p.28; Urribari et al., 2018, p.396). Central to this shift is the deployment of sophisticated Battery Health Management Systems (BHMS), which continuously monitor and predict critical battery states, including State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL) (Darbari, 20241; Ibrahim et al., 2023, pp.6-7; Issa et al., 2023, p.2). The rapid evolution of EV battery manufacturing is marked by increasing project complexity arising from tightly interdependent technical components and the involvement of multiple specialized stakeholders, making advanced management mechanisms such as DTs; effectively an impeccable aiding tool for facilitating organizational decision making and enhancing situational awareness(Acharya et al., 2024,p.2; Rosen & Pattipati, 2023, p.600). For this thesis scope, only integration challenges of BHMS related to multi-physics model will be discussed and the data interoperability issues impact on such projects risk management will be further explored. An illustrative DT representation BHMS has been depicted in Figure 4.1:

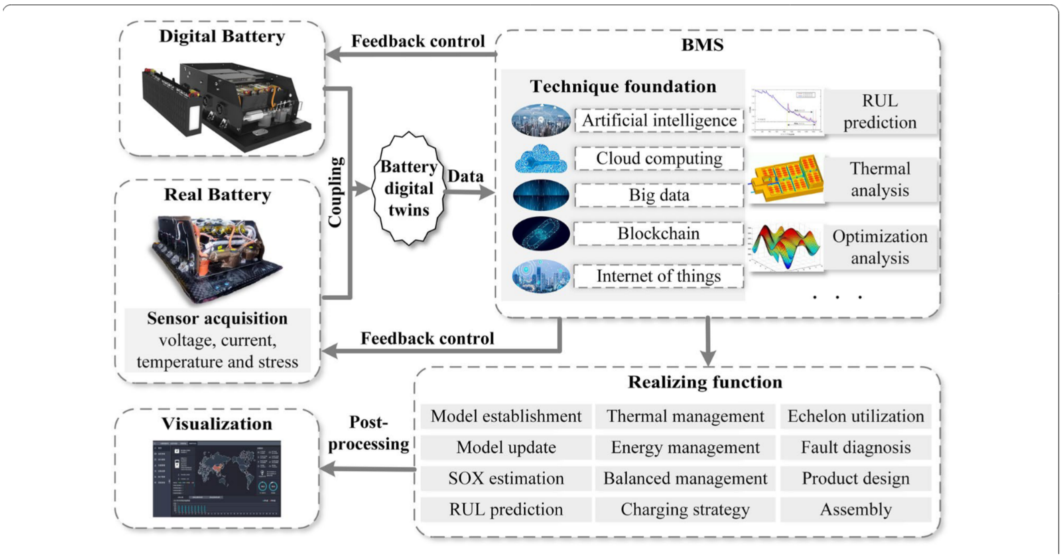

Figure 4.1. Illustrations of a representational Digital twin Model (Zhang, 2024, p.4).

4.1 Multi-physics model development in EV BHMS

Multiphysics simulation involves the concurrent modelling of multiple interacting physical phenomena—such as electrochemical, thermal, mechanical, and electrical behaviours—within a single computational framework to predict how a system will behave under realistic operating conditions (Anandavel et al., 2021,p.359; Singh et al., 2021,pp.8,17). As Anandeval et al. (2021,p.359) elaborated that, in the development of Ev batteries, this capability is absolutely essential because the performance, safety, and degradation traits of a lithium-ion cell cannot be fully understood by looking at just one physical domain in isolation. The complex electrochemical reactions that store and release energy are tightly linked with thermal dynamics that control heat generation, and both of these processes are directly influenced by mechanical stresses that change over the battery's lifetime (Anandavel et al.,2021,p.360; Singh et al.,2021,p.17).

The commercial urgency behind using these advanced models is highly significant. Batteries are the primary contributor to the overall cost of electric vehicles, with the production of battery cells alone accounting for 70 percent of the total cost of the battery pack (Siemens,2023,p.4).Hence, Manufacturers must simultaneously optimize the cell chemistry for better energy density, design advanced thermal management systems to prevent overheating and thermal runaway, and ensure that the production processes can consistently deliver high-quality cells on a massive scale. Traditional battery R&D relies on trial-and-error methods that lead to high time consumption and the wastage of expensive raw materials (Anandavel et al., 2021,p.361).This outdated development approach is no longer compatible with the fast pace that the modern automotive industry demands. However, the author documented evidence that by integrating these multi-physics models into a cloud server, project teams can test, simulate, and optimize battery performance in an entirely virtual environment by utilising DT, identifying and repairing design flaws before physical manufacturing begins as depicted in Figure 4.2:

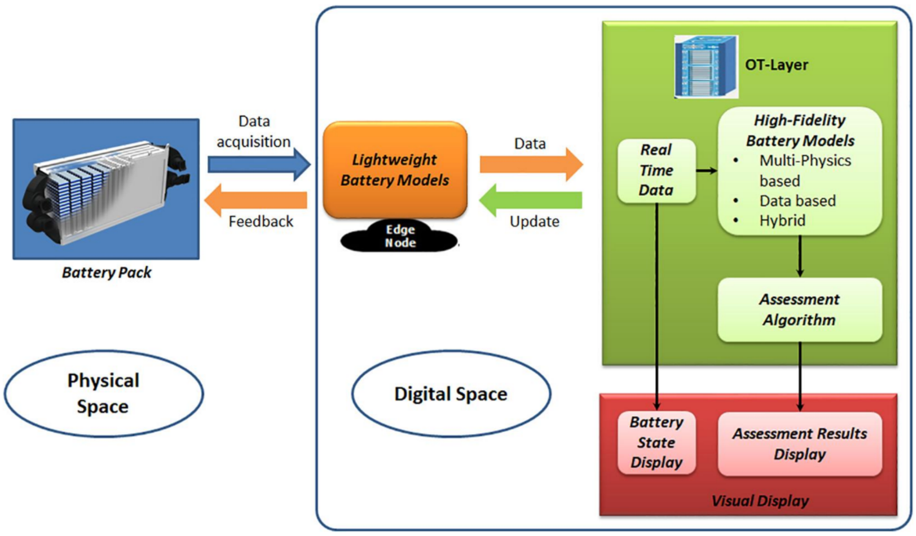

Figure 4.2. Framework of the digital twins in IoT (Anandavel et al., 2021, p.361).

Vehicle development cycles have become highly condensed having the same urgency of delivering the same quality, reliability and safety for customers within shorter timeline, forcing companies to design products of much greater complexity in far less time than in the past (Kocchar, 2023,p.781). This rush is driven by intense competitive pressure, strict environmental regulations aimed at meeting global climate goals, and shifting expectations from customers for smarter, high-performance vehicles (Kinman & Tutt,2023,p.251). As Kinman & Tutt

(2023,p.227) further reiterates, that manufacturers must move away from traditional, step-by-step engineering methods and adopt concurrent, digitally-driven development to meet this compressed schedule. This involves a ”shift left” strategy (Kinman & Tutt,2023,p.236), which means moving computer-aided engineering and critical decision-making much earlier in the design process. Multiphysics simulation, when embedded within a digital twin architecture, makes this shift possible. It allows engineering teams to virtually test, validate, and optimize battery designs instead of waiting to build physical prototypes and this dramatically reduces both development time and costs, avoids the waste of physical materials, and greatly increases design confidence long before any physical hardware is actually manufactured (Grieves,2023,p.111; Kinman & Tutt,2023,p.231).

4.1.1 Case study background of Rapid-protoyping and designing of the EV BHMS Multi-physics model development in Project Management context

The primary hurdle for developing multi-physics models in a project context remains computational complexity paired with the difficulty of parameterization, compounded by the challenge of integrating fragmented tool ecosystems. High-fidelity multi-physics models (such as 3D electrochemical or Pseudo-2D models) rely on highly non-linear and strongly coupled partial differential equations to simulate battery chemistry and physics (Naseri et al.,2023,p.10; Wang et al.,2021,p.5). These are too computationally heavy to run in real-time on a vehicle’s local Battery Management System (BMS)(Andavel et al.,2021,p.360). While the onboard system can easily run lightweight models like equivalent circuit models (ECMs), ECMs lack physical meaning and cannot accurately characterize internal electrochemical dynamics under varying operating conditions when used on their own (Singh et al.,2021, p.7 ; Wang et al.,2021,p.5) . This creates the central technical contradiction of the BHMS program: models precise enough to capture internal physical states cannot run on the limited onboard hardware, and models simple enough to run at the edge lack physical accuracy. Furthermore, accurately obtaining and continuously updating the internal parameters for these models as the battery ages is incredibly difficult, often requiring time-consuming or destructive laboratory testing (Wang et al.,2021,pp.5,7). The industry response is a hybrid digital twin architecture that resolves this contradiction. It pairs a lightweight edge model on the vehicle with high-fidelity, computationally intensive models hosted in the cloud. The cloud twin runs the heavy multi-physics simulations and periodically updates the parameters of the edge model, allowing the onboard system to make quick, localized decisions with cloud-level accuracy without exceeding its processing limits(Issa et al., 2023; Naseri et al., 2023; Wang et al., 2021). Additionally, this DT infrastructure serves as a virtual prototyping platform during the R&D phase, replacing expensive and wasteful physical trial-and-error testing with digital simulation and validation, significantly accelerating the development cycle and reducing costs (Andavel et al.,2021).

As Anandeval et al. (2021,p.360) elaborates ,during the initial project phases, teams develop physics-based models (such as the Newman model, which uses differential equations for mass and charge transport) to simulate current and future battery performance. When different teams and vendors try to merge their specific models and data streams, the lack of industry-wide communication standards creates severe interoperability bottlenecks (Darbari,2024,p.6).

4.2 The case Project from Literature review

An EV manufacturer initiating a Battery Health Management System (BHMS) program must deliver a system that predicts safety-critical states: State-of-Charge (SOC), State-of-Health (SOH), and Remaining Useful Life (RUL). Inaccuracies in SOC and SOH are unacceptable because they compromise safety, shorten cycle life, and reduce the vehicle's reliable range. Incorrect estimation allows the battery to operate outside safe limits, which can cause severe degradation or catastrophic thermal runaway leading to fire or explosion.

DT implementations aim for achieving much higher accuracy, with cloud-based systems reporting Mean Absolute Errors (MAE) of around 0.49% to 2% for SOC and between 0.74% and 2.3% for SOH (Naseri et al.,2023,p.4 ;Wang et al.,2021,p.13).

However, building hybrid-twin architecture introduces a project-level problem that the technical literature has not adequately addressed. Delivering the project requires four fundamentally different stakeholder groups — electrochemical modellers, embedded BMS engineers, cloud and AI platform developers, and OEM vehicle integration engineers — each working within its own tool ecosystem, data conventions, and organisational priorities. There is no shared industry standard governing how these groups should structure, label, or exchange the data that flows between their respective contributions (Darbari, 2024; Naseri et al., 2023; Singh et al., 2021). Every boundary between teams is therefore an ungoverned interface where the project can fail — not because any single team is performing poorly, but because the data handoffs between them are unmanaged. The BHMS project operates in an environment where the underlying cell chemistry is not fixed for the program's lifetime. Supplier formulation updates, dual-sourcing strategies for supply chain resilience, and evolving regulatory requirements can all alter the cell chemistry the system must model. Whenever this occurs, the high-fidelity multi-physics models at the core of the twin must be re-parameterised — a process that demands extensive laboratory campaigns, with battery conditioning alone taking up to three weeks. Every downstream team must then re-validate its models, retrain its algorithms, and re-test its interfaces against the new parameter set. The data interoperability challenge is therefore not a one-time integration task solved during initial development; it is a structural and recurring project risk that resurfaces each time the underlying cell data changes. This recurring nature is what makes it a risk management problem rather than purely a technical one. The time pressure under which this project operates compounds the risk. Vehicle development cycles have compressed historically as mentioned above, leaving almost no margin for the integration rework that results when four teams build in parallel and discover at system integration that their outputs do not combine. The project faces a situation where the tool intended to accelerate development — the digital twin — becomes the source of its most disruptive delays, because the data interoperability problems between the teams that build it were neither identified nor managed at the outset.

4.2.1 Project Objective

This thesis examines the project management challenges involved in delivering a hybrid digital twin-based Battery Health Management System (BHMS) for electric vehicles. Such a program is not executed by a single team; it requires coordinated work across four interdependent stakeholder groups — electrochemical modellers and battery cell researchers, embedded BMS engineers, cloud and AI platform developers, and OEM vehicle integration engineers — each operating in its own tool ecosystem, following its own data conventions, and producing deliverables that must integrate into a unified twin through ungoverned data interfaces. The project operates in an environment where the underlying cell chemistry is not fixed for the program's lifetime, meaning that supplier formulation changes, regulatory shifts, or dual-sourcing decisions can force the re-parameterisation of the entire model chain and the re-validation of every inter-team data interface — making data interoperability a recurring structural risk rather than a one-time integration task. The objective of this thesis is to identify the key data interoperability challenges that arise during the BMS design phase, analyse how these challenges translate into traceable project-level risks using structured planning tools such as Work Breakdown Structure (WBS), Design Structure Matrix (DSM), and Risk Breakdown Structure (RBS), and design a conceptual Project Digital Twin (PDT) model that can monitor and control these risks as a coordination instrument integrated into the project's governance structure.

4.2.2 Stakeholders and Project Deliverables

- **The Electrochemical Modelling and Battery Cell Research Group**: This team is responsible for the foundational science of the battery. Because the internal chemical reactions of a lithium-ion battery are incredibly complex, this group builds high-fidelity ”heavy-weight” models, as mentioned above. These models mathematically simulate the complex chemical, electrical, and thermal behaviors that occur inside the battery cell.

  To build these advanced simulations, the researchers use highly specialized software tools like COMSOL Multiphysics and PyBaMM. Their main job is to understand how the battery ages over time by analyzing degradation factors like lithium plating or the growth of internal resistance.

  - **Deliverables and data exchange**: This group cannot put their massive models directly into the car. Instead, they deliver validated testing reports, degradation profiles, and carefully calibrated ”parameter sets”. These parameters are the mathematical instructions that are handed off to the software teams so that the smaller, onboard vehicle models can accurately understand the battery’s chemistry.

- **The Embedded BMS and Edge Engineering Group**: This group works at the ”edge,” meaning they build the technology that lives physically inside the vehicle. Their primary workspace is the onboard Battery Management System (BMS), which runs on a small microprocessor with very limited memory and processing power. Because the vehicle’s computer must make safety-critical decisions in milliseconds, this team cannot use the heavy chemical models built by the research group. Instead, they build ”lightweight” models (like Equivalent Circuit Models) that run fast and efficiently on the car’s hardware.

  - **Deliverables and Data Exchange:** The embedded engineering team is responsible for capturing the real-world physical data. They develop the logic to gather continuous sensor data streams, primarily measuring voltage, current, and temperature, and sometimes even mechanical stress or strain using specialized fiber sensors. Their main deliverable is the firmware that runs on the vehicle, and they are responsible for continuously transmitting these clean sensor data streams upward to the cloud for heavy analysis.

- **The Cloud Platform and AI Development Group**: This group handles the heavy computing work that the car itself cannot perform. They build and maintain the digital twin on powerful cloud platforms, frequently utilizing services like Microsoft Azure or Amazon Web Services (AWS). Because they have access to massive cloud computing power, this team uses Artificial Intelligence (AI) and Machine Learning (ML) algorithms to process the massive amounts of sensor data being streamed from the vehicles.
  - **Deliverables and Data Exchange:** This team builds the data ingestion pipelines to collect the car's data and visualizes the battery's health on assessment dashboards for human operators to monitor. Their most critical deliverable is sending information back down to the vehicle. By running heavy simulations in the cloud, they calculate accurate estimates for the State of Charge (SoC), State of Health (SoH), and Remaining Useful Life (RUL). They regularly push these updated, highly accurate parameters back down to the embedded engineering group's edge model in a continuous data loop, ensuring the car's lightweight model stays accurate as the battery ages.
- **The OEM Vehicle Integration Group** :This group acts as the central coordinator, tying all the isolated technologies and teams together into the final electric vehicle product. They manage the project using Product Lifecycle Management (PLM) software platforms, such as Siemens Teamcenter, to bridge the gap between design, research, and actual factory manufacturing. Modern electric vehicles consist of incredibly diverse parameters, and ensuring that different software from various technology providers and automakers can actually communicate with one another is a major challenge.
  - **Deliverables and Data Exchange:**This team is responsible for managing the overall architecture and ensuring system compatibility.If a battery supplier changes the internal cell chemistry or materials, this group issues revision notices and updates the external interface specifications. They deliver these crucial updates to the other three engineering teams, ensuring that the research group re-tests the chemistry, the cloud group updates the AI algorithms, and the embedded group adjusts the car's sensors so that the entire unified twin continues to function smoothly.

Table 4.1. Stakeholder Groups, Deliverables, Data Exchange, Interoperability Risks and Classification.

Stakeholder Group	Key Deliverables	Data Exchanged	Interoperability Risk	Risk Type (Source)
Electrochemical Modelling Group	Validated multi-physics outputs; degradation parameters; revised parameter sets	*Sends:* simulation outputs, parameter sets. *Receives:* cell specs; sensor data for calibration	Simulation outputs in COMSOL/PyBaMM formats incompatible with cloud pipeline; no shared standard; recurs each re-parameterization	**Syntactic; Organizational** (Anandavel et al.,2021; Ibrahim et al., 2023; Singh et al., 2021)
Embedded BMS and Edge Engineering Group	Lightweight edge software; sensor acquisition logic; SoC estimator; BMS control algorithms	*Sends:* sensor streams in hardware-encoded formats. *Receives:* updated model parameters	Hardware-encoded data requires custom translation at cloud boundary; communication delays cause timestamp mismatches	**Syntactic; Dynamic** (Li et al., 2021; Singh et al., 2021; Suganya et al., 2024)
Cloud Platform and AI Development Group	Trained digital twin models; data pipeline; updated parameters pushed to edge; operator dashboards	*Sends:* retrained parameters to edge. *Receives:* sensor streams; parameter sets from modelling group	Must reconcile incompatible formats from two groups simultaneously; synchronization fails under delays; retraining recurs each chemistry update	**Semantic; Pragmatic; Dynamic** (Issa et al., 2023; Naseri et al.,2023; Wang et al.,2021)
OEM Vehicle Integration Group	Integrated vehicle platform; verification documentation; external interface specs; supplier change notifications	*Sends:* interface requirements and supplier updates to all groups. *Receives:* deliverables from all three groups	No cross-manufacturer data standard exists; all unresolved failures surface simultaneously at system integration	**Technical; Organizational** (Darbari, 2024; Naseri et al., 2023; Verma et al.,2024)

4.2.3 The Interoperability Risks Identified between edge and cloud: Research Objective 1

Before exploring into EV bhms case, a similar article published by Acharya et al. (2024) gives us overview of a case where they provided a real project called GoRI which was funded by the Academy of Finland, a hybrid Vehicle-in-the-loop (VIL) setup at NUVE lab was being developed to test and validate advanced autonomous driving features. During the project, the engineers noticed a specific symptom: the tractor model and the dynamometer could not successfully synchronize their real-time torque and speed data. By looking closely at this symptom, they observed that the different machines used diverse data formats and mismatched communication protocols, which ruined the real-time timing. Using the framework, the engineers detected that they were facing a combination of Technical (mismatched protocols), Syntactic (different data formats), and Dynamic (failure to synchronize in real-time) interoperability problems. By mapping what they saw going wrong to the specific definitions in the framework, they were able to pinpoint the exact nature of their integration hurdles and figure out which targeted solutions to apply.Due to lack of sufficient literature, this was the method that was adopted for identifying the actual risks during project.

Now, different types of Interoperability risks identified will be discussed below:

- **Level 1 — Technical interoperability:** basic connectivity and infrastructure. Acharya et al. (2024) state that technical interoperability problems are detectable when the project struggles with the physical or foundational digital connection between systems — including mismatched communication protocols and middleware failures. In the BHMS case, Table 4.1 documents this at the OEM vehicle integration boundary: no cross-manufacturer data standard exists for the exchange of deliverables between the four teams, and the platforms used by different stakeholder groups (COMSOL, Azure/AWS, Teamcenter) lack a common communication protocol governing how their outputs connect at the infrastructure level (Darbari, 2024; Naseri et al., 2023; Verma et al., 2024). The symptom is that all unresolved technical failures surface simultaneously at system integration, because no shared infrastructure layer detected them earlier. In project management terms: This is a technical risk that directly threatens milestone delivery. Because the infrastructure-level incompatibility is invisible during parallel development, it manifests only at the integration gate — the point at which schedule float has already been consumed and corrective action is most expensive.

- **Level 2 — Syntactic interoperability:** format and structure. Acharya et al. (2024) state that syntactic problems are detectable when systems are connected but cannot read or parse each other's data structures — visible as misaligned schemas, inconsistent metadata, or constant need for format translation. In the BHMS case, Table 4.1 documents this at two boundaries. At the electrochemical modelling boundary, simulation outputs generated in COMSOL and PyBaMM are not natively consumable by the cloud pipeline, requiring bilateral format translation at every handoff — and this translation recurs each time re-parameterisation is triggered by a chemistry change (Singh et al., 2021; Anandavel et al., 2021; Ibrahim et al., 2023). At the embedded BMS boundary, the edge team encodes sensor streams in hardware-optimised formats that the cloud boundary cannot ingest without custom translation (Li et al., 2021; Singh et al., 2021; Suganya et al., 2024). In project management terms: This is an integration management breakdown that introduces cost risk. The translation effort is unplanned, recurring, and invisible in the project schedule until it surfaces as delay. Each re-parameterisation cycle reproduces the same translation burden, compounding cost over the program's lifetime.

- **Level 3 — Semantic interoperability:** meaning and context. Acharya et al. (2024) state that semantic problems are detectable when systems can exchange and parse files but disagree on what the data actually means — visible as confusion over vocabulary, missing ontologies, or failure to carry data context across systems. In the BHMS case, Table 4.1 documents this at the cloud platform boundary: the cloud team must reconcile data arriving simultaneously from the modelling group and the edge group, where the same physical quantities (voltage, temperature, state variables) may carry different measurement conventions, reference frames, or calibration assumptions depending on which team produced them (Issa et al., 2023; Naseri et al., 2023; Wang et al., 2021). Without a shared ontology binding the four teams to common definitions, the cloud model risks misinterpreting the meaning of its inputs — a misinterpretation that propagates silently into the SoC and SoH estimates the program is committed to deliver. In project management terms: This is a quality risk that produces error propagation. Misinterpretation at the semantic level is not caught by syntactic validation (the data parses correctly) and surfaces only when the twin's outputs fall outside the acceptance thresholds — by which time the source of the error is difficult to trace back to a specific handoff.

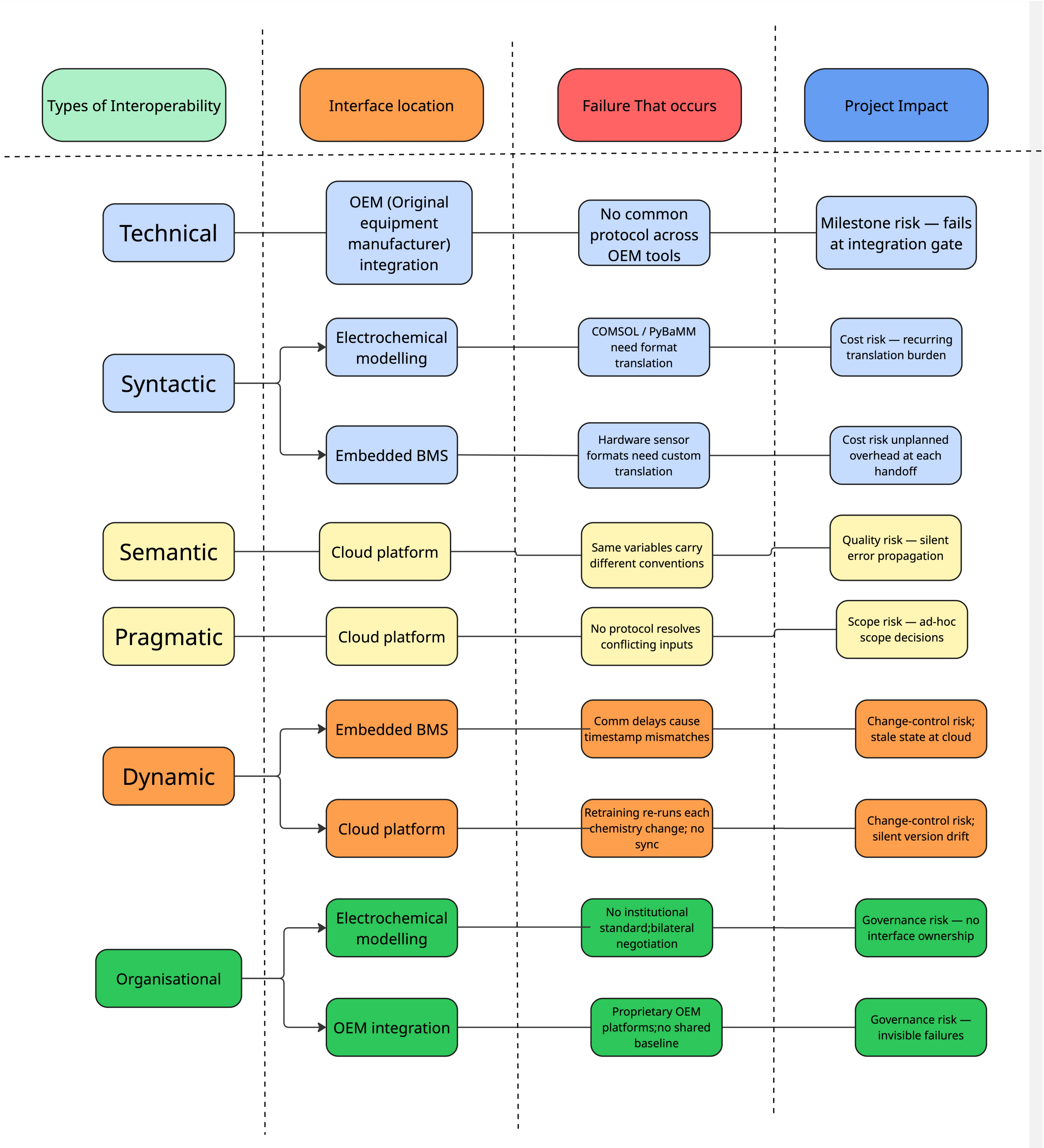

Figure 4.3. Type of Interoperability Failures and Project Impact on EV BHMS case (Adopted from 11 selected literature related to EV BHMS mentioned in methodology section .

- **Level 4 — Pragmatic interoperability:** usability and operational workflow. Acharya et al. (2024) state that pragmatic problems are detectable when data is connected, formatted, and understood, but still cannot be used effectively to perform operations — visible as workflow failures, inability to trigger correct actions, or lack of automated orchestration. In the BHMS case, Table 4.1 documents this at the cloud platform boundary: the cloud team receives data from both the modelling group and the edge group, and these two incoming streams serve fundamentally different operational purposes — the parameter sets calibrate the model, while the sensor streams validate it — yet no workflow protocol governs how conflicting signals between the two should be resolved (Issa et al., 2023; Naseri et al., 2023; Wang et al., 2021; Verma et al., 2024). The symptom is that the cloud team must make ad-hoc judgements about which input to trust when they diverge, rather than following a governed decision protocol. In project management terms: This is a scope risk. When two inputs serve different purposes but arrive at the same consuming team without an explicit protocol, each ad-hoc resolution is an uncontrolled scope decision — the team is implicitly redefining what the deliverable means each time it resolves a conflict, without that redefinition being visible to the project manager.

- **Level 5 — Dynamic interoperability:** real-time adaptability to change. Acharya et al. (2024) state that dynamic problems are detectable when the system works in a static environment but fails when conditions change — visible as synchronisation failures, inability to process changing data in real time, and failure to adapt to new conditions. In the BHMS case, Table 4.1 documents this at two boundaries. At the embedded BMS boundary, communication delays cause timestamp mismatches between edge and cloud, meaning the cloud model receives data that no longer reflects the battery's current state (Li et al., 2021; Singh et al., 2021; Suganya et al., 2024). At the cloud platform boundary, synchronisation fails under latency, and the entire retraining workflow must re-execute each time the underlying cell chemistry is updated — with no mechanism ensuring all four teams are synchronised to the same chemistry revision simultaneously (Issa et al., 2023; Wang et al., 2021; Naseri et al., 2023). In project management terms: This is a change-control risk. Each chemistry change is, in PMBOK (2017) terms, a scope and configuration change request whose impact propagates simultaneously across all four teams. The absence of a synchronisation mechanism means the project has no way to verify that all teams are working against the same baseline at any given point — a condition that produces silent version drift detectable only at integration.

- **Level 6 — Organisational interoperability:** governance and alignment. Acharya et al.

(2024) state that organisational problems are detectable when the technology works but human teams, vendor companies, or business structures fail to align — visible as policy clashes, fragmented processes, data governance disputes, and failure to align technical strategy with business objectives. In the BHMS case, Table 4.1 documents this at two boundaries. At the electrochemical modelling boundary, the absence of a shared standard means each handoff is governed by bilateral negotiation rather than by an institutional protocol (Singh et al., 2021; Anandavel et al., 2021; Ibrahim et al., 2023). At the OEM integration boundary, proprietary platforms used by different manufacturers deepen the governance gap, and no cross-team configuration baseline binds the four groups to a common chemistry revision (Darbari, 2024; Naseri et al., 2023; Verma et al., 2024). No single stakeholder owns the interfaces between the teams. In project management terms: This is a governance risk. Without interface ownership, failures accumulate invisibly across the program because no monitoring instrument tracks cross-team interface status. The project manager has no structured means of knowing which interfaces have been validated, which parameter sets are current across all four teams, or whether an upstream change has been acknowledged by all downstream consumers.

4.2.4 The Project Impact Identification: Research Objective 2 & 3

As per my thesis scope before creating dsm, wbs will be required to map and place identified tasks into structured format. Those tasks are iteration of previously described tasks.

4.2.5 The WBS

A deliverables-oriented Work Breakdown Structure was adopted for the BHMS development project. Goetsch (2015, p.63) identifies four WBS formats commonly used in engineering and technology projects namely deliverables oriented, verb oriented, noun oriented, and time phased. The author recommends the deliverables format unless the project duration necessitates phased planning. In the Table 4.2, deliverables oriented format was selected over the

verb oriented alternative because the BHMS project involves four distinct stakeholder groups developing components in parallel isolation using incompatible tool ecosystems, and a verb-oriented WBS would group all teams under shared action phases such as ”design” or ”test,” thereby concealing the very organizational boundaries where data interoperability failures materialize. As Bissonette (2016, p.100) asserts, the WBS establishes unambiguous administrative ownership for each deliverable at the technical and physical boundaries where work occurs. This is consistent with the mirroring principle established by Whyte and Davies (2021, p.4), who demonstrated that the organizational structure of a project mirrors the architecture of the technical system being built. Consequently, by organizing the major deliverable groups by stakeholder group, each WBS boundary directly corresponds to an organizational interface where interoperability failures are most likely to emerge. These boundaries are then screened against the six-level interoperability taxonomy proposed by Acharya et al. (2024, p.6), following the Phase 1 procedure developed in Section 2.5. The decomposition follows the 100 percent rule (Goetsch, 2015, p.64), ensuring that all major deliverables collectively represent the complete project scope. The resulting work packages, each assigned a unique task identifier, serve as the input elements for the Dependency Structure Matrix constructed in the subsequent section. In the Table 4.2 the whole WBS package has been demonstrated. The icon ”$\rightarrow$” means ”sends output to” — for example, T4 (P2D model development) shows $\rightarrow$ T14 (The cloud team can’t build their synchronization engine without receiving high-fidelity electrochemical model output from Battery R&D.) whereas ”$\leftarrow$” means ”receives input from” — for example, T12 (data ingestion pipeline) shows $\leftarrow$ T10 because the cloud pipeline can’t be designed until it knows what data format the edge telemetry (T10) will send.

Table 4.2. WBS for Digital Twin-based EV BHMS.

WBS	ID	Task	Owner	Handoff	Data relevance to Project Manager
1.2 Electromechanical model development					
1.2.1	T1	Cell parameter characterization	Battery R&D	–	Inaccurate cell parameters propagate errors to all downstream models, causing rework during integration.
1.2.2	T2	P2D / DFN model development (COMSOL / PyBaMM)	Battery R&D	$\rightarrow$ T12	COMSOL output must be translated to Python for cloud — format incompatibility causes integration (schedule) delay.
1.2.3	T3	Aging & degradation calibration	Battery R&D	–	Inaccurate aging model produces unreliable RUL predictions, undermining stakeholder trust in the DT.
1.2.4	T4	Model order reduction (ROM) for edge	Battery R&D	$\rightarrow$ T5	ROM parameters exported to embedded team may use different naming conventions and units, causing misinterpretation and rework.
1.3 Edge BMS / embedded model					
1.3.1	T5	ECM design & parameterization	Embedded	$\leftarrow$ T4	Cannot start until Battery R&D delivers ROM— delay here pushes entire integration timeline.
1.3.2	T6	Real-time SoC / SoH estimation algorithm	Embedded	–	Inaccurate SoC estimation produces unreliable battery state data, compromising digital twin fidelity.
1.3.3	T7	Thermal monitoring & safety logic	Embedded	$\rightarrow$ T17	If thermal runaway detection thresholds on edge differ from cloud predictions, safety compliance verification fails.
1.3.4	T8	Edge-to-cloud telemetry protocol	Embedded	$\rightarrow$ T10	Edge transmits compressed data that cloud cannot interpret without semantic context —data quality degrades, causing inaccurate cloud model predictions.
1.4 Cloud DT platform					
1.4.1	T9	Cloud infrastructure provisioning	Cloud/AI	–	All cloud development tasks depend on infrastructure being ready — delay shifts entire cloud workstream.
1.4.2	T10	Data ingestion pipeline	Cloud/AI	$\leftarrow$ T8	Pipeline design depends on edge telemetry format — if format is incompatible, pipeline requires redesign causing schedule delay.
1.4.3	T11	AI/ML model training (RUL prediction)	Cloud/AI	–	Inaccurate RUL predictions reduce digital twin value—stakeholders lose confidence in predictive maintenance capability.
1.4.4	T12	Twin synchronization engine	Cloud/AI	$\leftarrow$ T2	Sync engine must translate electrochemical model from COMSOL to Python — format incompatibility causes integration delay and potential accuracy loss.
1.5 Supplier data integration					
1.5.1	T13	Cell specification acquisition	Supplier	–	Supplier delivery timeline is outside project control — late delivery delays all Battery R&D parameterization work.
1.5.2	T14	Black-box model interface specification	Supplier	$\rightarrow$ T1	Supplier's proprietary parameter definitions create semantic gap with internal models — discovered late during integration, causing costly rework
1.6 System integration & validation					
1.6.1	T15	Edge-to-cloud integration testing	Cloud/AI	$\leftarrow$ T8,T10	All parallel workstreams converge here — schedule is dictated by the slowest interface resolution, causing project delay.
1.6.2	T16	Hybrid twin merge: physics + data-driven	Cloud/AI	$\leftarrow$ T2,T11	If physics-based and data-driven models produce conflicting outputs after merge, digital twin becomes untrustworthy for decision-making.
1.6.3	T17	Safety compliance verification	Embedded	$\leftarrow$ T7,T12	If edge thermal safety thresholds and cloud predictive model disagree on anomaly definition, safety certification fails.
1.6.4	T18	Stakeholder acceptance testing	PM	–	Final gate — PM coordinates sign-off across all stakeholder groups before deployment.
1.7 Deployment & lifecycle					
1.7.1	T19	Documentation & knowledge transfer	PM	–	Captures all interoperability standards and integration decisions for lifecycle maintenance.

4.2.6 The DSM

Having established the WBS decomposition with its explicit handoff dependencies in Table 4.2, the process architecture DSM is now constructed to map the full network of information dependencies among the 19 project tasks. While the WBS captures hierarchical scope ownership and direct handoffs, it does not reveal the lateral, cross-boundary interdependencies and feedback loops that are the primary sites of interoperability failure in complex DT projects (Eppinger & Browning, 2012, pp.130- 133; Gálvez et al., 2015, p.72). The DSM addresses this gap by representing each task as both a row and a column in a square matrix, where a mark in cell (i, j) indicates that task i requires information from task j to complete its work. The matrix follows the IR/FAD convention (inputs in rows, feedback above the diagonal) as defined by Eppinger and Browning (2012, p.131).

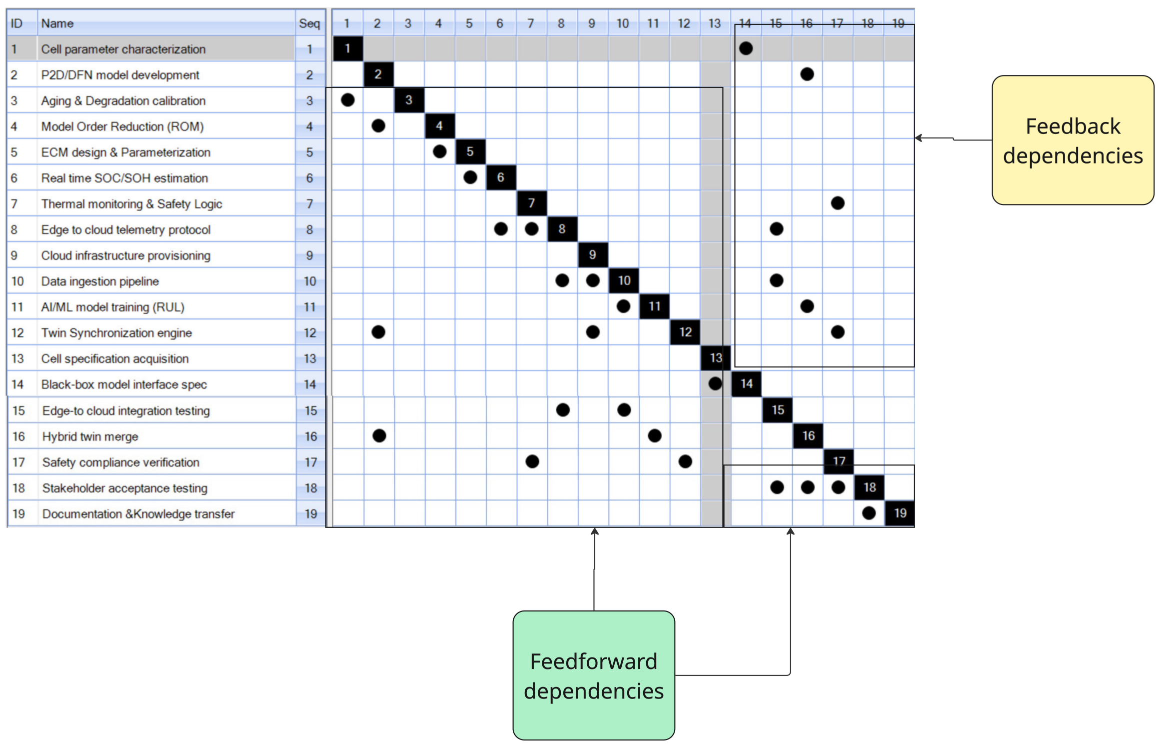

Figure 4.4. Process Architecture DSM for the EV BHMS Digital Twin Project (Plotted in DSMmatrix software).

4.2.7 DSM Analysis: Identifying Coupled Tasks and Interoperability Risk Propagation Pathways

- **Sequential and parallel relationships:**The majority of the 22 feedforward marks below the diagonal confirm that the BHMS project follows a broadly sequential flow: Battery R&D tasks (T1–T4) feed into Embedded tasks (T5–T8), which feed into Cloud/AI tasks (T9–T12), converging at integration (T15–T17) before acceptance and deployment (T18–T19). Within each stakeholder group, tasks are largely sequential: T1 feeds T3 (aging calibration depends on cell parameters), T3 informs T4 (ROM requires a validated full model), and T4 feeds T5 (embedded ECM depends on the reduced-order model). Similarly, T5 feeds T6, and T6 and T7 jointly feed T8. The Cloud/AI group shows a parallel structure where T10 and T12 can proceed simultaneously once their respective upstream inputs (T8 and T2) are available, both depending on infrastructure provisioning T9.
- **Feedback loops and coupled tasks:** The seven feedback marks above the diagonal are the critical findings of this DSM, as they represent the coupled task relationships where iterative rework and therefore interoperability failure propagation will occur. Three distinct feedback circuits are identified.

- **Supplier–Battery R&D loop (T1 $\leftarrow$ T14):** Cell parameter characterization (T1) must begin before the supplier delivers the black-box model interface specification (T14), because Battery R&D cannot wait for supplier timelines that are outside project control. However, when T14 is finally delivered, its proprietary parameter definitions may conflict with the assumptions already embedded in T1, forcing rework. This is a cross-boundary semantic interoperability risk (Level 3, Acharya et al., 2024): the supplier and Battery R&D use different naming conventions, units, or reference frames for the same electrochemical parameters. The DSM makes explicit that this feedback crosses two organisational boundaries (Supplier $\rightarrow$ Battery R&D), meaning the rework propagates forward through T3, T4, and all downstream tasks that depend on parameterisation output.
- **Integration–Edge/Cloud loop (T8 $\leftarrow$ T15, T10 $\leftarrow$ T15):** Edge-to-cloud integration testing (T15) depends on both the telemetry protocol (T8) and the data ingestion pipeline (T10), but when integration tests reveal failures, they force rework on both T8 and T10. This

creates a coupled block spanning two stakeholder groups: the Embedded team owns T8 while the Cloud/AI team owns T10, yet neither can resolve their rework independently because the integration failure typically involves syntactic incompatibility (Level 2) or dynamic synchronisation failure (Level 5) at the edge–cloud interface. This feedback circuit is the most operationally expensive one identified, because rework on T8 or T10 cascades forward through T11, T12, T15, T16, and T17 before reaching T18.

- **Validation–Design loops (T2 $\leftarrow$ T16, T11 $\leftarrow$ T16, T7 $\leftarrow$ T17, T12 $\leftarrow$ T17):** The hybrid twin merge (T16) and safety compliance verification (T17) are late-stage validation tasks that generate feedback to early-stage design tasks. When the physics-based and data-driven models produce conflicting outputs after merge at T16, the root cause may lie in the P2D model (T2) or in the ML training (T11), forcing rework on either or both. Similarly, when safety compliance verification (T17) reveals that edge thermal thresholds and cloud predictive models disagree on anomaly definition, this forces rework on thermal monitoring logic (T7) and the twin synchronization engine (T12). These are long feedback loops — spanning 10+ tasks in the sequence — and as Eppinger (2001) warns, long feedbacks are especially problematic because many interim tasks will have proceeded with assumptions that are now invalidated, precipitating a cascade of rework through the process. Cross-boundary dependency concentration. The DSM reveals that 12 of the 29 total information dependencies cross stakeholder group boundaries. Of these, all seven feedback marks (O) are cross-boundary dependencies. This confirms the theoretical argument established in Section 2.4: interoperability failures materialise at the interfaces between organisational domains, and it is precisely the coupled, cross-boundary tasks that are most vulnerable to the syntactic, semantic, and organisational mismatches identified through the Acharya et al. (2024) taxonomy in Section 4.2.3. No feedback loop in this DSM is contained within a single stakeholder group, meaning that every iteration requires cross-team coordination and information exchange the exact conditions under which interoperability failures are most costly and most likely to remain undetected until integration (Cooper et al., 2005, p.49).

Mapping feedback loops to interoperability risk levels and the three-phase framework. Each feedback mark in the DSM corresponds to a specific interoperability risk level from the RBS and a specific propagation pathway through the project plan, directly enabling the Phase 1 pre-deployment risk structuring described in Section 2.5. Circuit 1 (T1 $\leftarrow$ T14) maps to Level 3 semantic and Level 6 organisational interoperability risk, with a propagation pathway through T1 $\rightarrow$ T3 $\rightarrow$ T4 $\rightarrow$ T5 $\rightarrow$ T6 $\rightarrow$ T8 $\rightarrow$ T10. Circuit 2 (T8/T10 $\leftarrow$ T15) maps to Level 2 syntactic and Level 5 dynamic interoperability risk, with propagation through the entire integration and validation chain. Circuit 3 (T2/T11 $\leftarrow$ T16 and T7/T12 $\leftarrow$ T17) maps to Level 3 semantic risk where physics-based and data-driven models interpret shared variables differently, with propagation pathways that reach back to the earliest design tasks. These mapped pathways provide the project manager with the structured impact traces required for Phase 2 monitoring: schedule variance in any task downstream of a feedback mark becomes an early-warning indicator that an interoperability failure is propagating through the dependency chain, enabling the level-specific response activation defined in Phase 3. Reading across any row reveals all the information inputs that task requires from other tasks; reading down any column reveals all the tasks to which that task provides output. Marks below the diagonal represent feedforward dependencies where information flows from an earlier task to a later one in the planned sequence. Marks above the diagonal represent feedback dependencies where a downstream task generates information that may force rework of a prior task — these are the coupled tasks whose iterations create the interoperability risks identified in Section 4.2.3.

4.2.8 The RBS

In this module, first the comparative analysis retrieved from the literature review will be discussed in this following Table 4.3 below: The core problem the PDT addresses In complex DT projects like the EV BHMS, interoperability failures between subsystems are rarely visible during parallel development phases. They remain latent within organizational boundaries until system integration forces incompatible outputs to converge — at which point their cost and schedule impact is most severe (Cooper et al., 2005, pp.30,49,66; Raydugin, 2013, p.100). Traditional project risk management relies heavily on periodic performance reviews, status reports, and manual checks (Bissonette, 2016, pp.58–60). The problem with this approach in a highly integrated project is that technical interoperability failures — such as data format mismatches or communication protocol errors — propagate instantly. By the time a project manager reads a periodic status report, the failure has already caused system downtime or rework. The cost of making changes increases over the project lifecycle, so the later these fail-

Table 4.3. Comparative analysis of RBS approaches in the literature..

Source	**Risk Categories**	**Formation Method**	**Orientation**	**Limitation for DT Projects**
PMBOK (2017)	Technical; Management; Commercial; External	Generic organizational template, tailored per project and documented in the risk management plan.	Template-driven, broad applicability	All interoperability failures collapse into one "Technical" bucket
Goetsch (2015)	External/Unpredictable; External/Predictable but uncertain; Internal/Technical; Internal/Nontechnical; Legal/Ethical	Four-step team process: form team, distribute RBS template, apply identification methods (brainstorming, SWOT, Delphi), produce cause-and-effect risk statements.	Team-facilitated, engineering projects	Internal/external split misses cross-boundary interface failures
Bissonette (2016)	Project plans; Project management controls; Communications; Leadership; Product development processes; Productivity and infrastructure tools; Resource availability; Business/External factors	Derived from fishbone diagram of causes of unsuccessful execution. Eight branches split into PM-influenced and organization-influenced groups, then flattened into a hierarchical tree.	Root-cause, socio-technical	Captures organizational causes but lacks technical granularity for DT data flows
Raydugin (2013)	Engineering; Procurement; Construction; Commissioning and startup; Operations; Regulatory; Stakeholders; Commercial; Partners; Interface management; Change management; Organizational	Context-adaptive: categories invented per project context using frameworks like PESTLE or POCET. Two-level structure with up to two dozen subcategories. Granularity set in the risk management plan.	Uncertainty-focused, project-specific	Adaptive philosophy fits, but specific categories target capital megaprojects
Rane et al. (2021)	Operational; Technical; Environmental; Design; Financial; Political	Literature survey identifies risks; expert panel (Delphi) codes and maps them to categories. Each coded risk mapped to Industry 4.0 monitoring technologies and sensor parameters.	Technology-integrated, Industry 4.0	Format is transferable; categories are construction-specific

ures surface, the more expensive correction becomes (Bissonette, 2016, p.23; Raydugin, 2013, pp.12,27,137). The specific gap your thesis identifies is this: Acharya et al. (2024) identified 77 interoperability challenges across six levels for DT in cyber-physical systems. But their framework is a diagnostic taxonomy — it tells you what types of interoperability problems exist, but it does not tell a project manager where in the project structure they will cause damage, who is responsible for resolving them, or how to respond. Existing project risk management frameworks do not account for data interoperability as a distinct, anticipatable category of project risk that can be systematically identified, monitored, and acted upon before it propagates into project-level consequences. How the PDT solves it — in three steps The PDT-enhanced PMIS closes this gap by converting Acharya et al.'s diagnostic taxonomy into a management instrument through the integration of three project management tools (WBS, DSM, RBS) across three sequential phases. Phase 1 solves the visibility problem. In traditional PRM, interoperability risks are discoverable only after they have caused damage — typically at the integration gate when all parallel workstreams converge. Phase 1 reverses this by screening every WBS work package that involves a data exchange against the six interoperability levels before any DT subsystem is deployed. For example, a work package involving data handoff between the electrochemical DT (Vendor A) and the thermal management DT (Vendor B) would be assessed for technical risk (protocol compatibility), syntactic risk (data format parsing), semantic risk (shared variable conventions), and organisational risk (governance alignment). These are registered as anticipatory risk entries in the RBS — not in generic terms like ”technical risk” but in precise, interface-specific formulations. The DSM then maps which downstream tasks depend on each flagged interface, establishing the propagation pathway a failure would follow. The output is a project information system pre-configured to recognise interoperability risk: a WBS with tagged interfaces, an RBS with level-specific entries, and a DSM with mapped impact pathways (Section 2.5, Phase 1). Phase 2 solves the translation problem. The project manager does not monitor the DT's internal data streams — that belongs to the engineering team. What the PM monitors are the project-level consequences of interoperability failures, observable through standard project management instruments. Five categories of indicators serve as monitoring signals: integration test pass/fail rates at tagged interfaces, deliverable rejection rates at interoperability-exposed work packages, frequency of interface specification change requests between vendor teams, schedule variance in work packages downstream of flagged data exchange points, and unresolved data interpretation disputes escalated during design reviews. Each indicator is linked back to specific interoperability levels through the RBS structure from Phase 1. A rising integration test failure rate points toward a Level 1 technical or Level 2 syntactic problem. Deliverable rejections where both subsystems pass individual validation but diverge on shared outputs suggest a Level 3 semantic problem. A surge in interface change requests between vendor teams suggests a Level 4 pragmatic or Level 6 organisational problem. The framework thereby translates engineering-level interoperability failures into the language of project management — schedule variance, rework frequency, and milestone risk — without requiring the PM to possess specialised data engineering expertise (Section 2.5, Phase 2). Phase 3 solves the response precision problem. In conventional risk management, a failed integration test would be classified under a broad category such as ”technical risk,” and the PM would assign an engineer to investigate on an ad hoc basis. The PDT framework replaces this with structured, level-specific response logic. A Level 1 technical failure triggers a protocol compatibility audit. A Level 2 syntactic failure triggers middleware reconfiguration. A Level 3 semantic failure triggers an ontological alignment session between domain teams — because the problem is a definitional inconsistency that debugging alone cannot resolve. A Level 4 pragmatic failure triggers workflow redesign. A Level 5 dynamic failure triggers an architecture review of real-time synchronisation mechanisms. A Level 6 organisational failure triggers escalation to senior management for governance realignment. This prevents the PM from spending weeks on code-level debugging when the actual root cause is a semantic convention mismatch, or from convening technical workshops when the problem is a governance misalignment that only contractual intervention can resolve (Section 2.5, Phase 3). By connecting the detected symptom (Phase 2) to a classified root cause (Phase 3) through the pre-structured RBS (Phase 1), the framework ensures each interoperability failure is met with the response category most likely to resolve it — reducing diagnostic delay, minimising misdirected corrective effort, and containing downstream impact on project schedule and cost. This is the operational contribution of the PDT: it transforms interoperability risk from an invisible, after-the-fact discovery into a structured, anticipatable, and level-specifically-addressable project management concern.

4.3 Applying the PDT framework

Phase 1 solves the visibility problem. In traditional PRM, interoperability risks are discoverable only after they have caused damage — typically at the integration gate when all parallel workstreams converge. Phase 1 reverses this by screening every WBS work package that involves a data exchange against the six interoperability levels before any DT subsystem is deployed. For example, a work package involving data handoff between the electrochemical DT (Vendor A) and the thermal management DT (Vendor B) would be assessed for technical risk (protocol compatibility), syntactic risk (data format parsing), semantic risk (shared variable conventions), and organisational risk (governance alignment). These are registered as anticipatory risk entries in the RBS — not in generic terms like ”technical risk” but in precise, interface-specific formulations. The DSM then maps which downstream tasks depend on each flagged interface, establishing the propagation pathway a failure would follow. The output is a project information system pre-configured to recognise interoperability risk: a WBS with tagged interfaces, an RBS with level-specific entries, and a DSM with mapped impact pathways (Section 2.5, Phase 1). Phase 2 solves the translation problem. The project manager does not monitor the DT's internal data streams as this belongs to the engineering team. What the PM monitors are the project-level consequences of interoperability failures, observable through standard project management instruments. Five categories of indicators serve as monitoring signals: integration test pass/fail rates at tagged interfaces, deliverable rejection rates at interoperability-exposed work packages, frequency of interface specification change requests between vendor teams, schedule variance in work packages downstream of flagged data exchange points, and unresolved data interpretation disputes escalated during design reviews. Each indicator is linked back to specific interoperability levels through the RBS structure from Phase 1. A rising integration test failure rate points toward a Level 1 technical or Level 2 syntactic problem. Deliverable rejections where both subsystems pass individual validation but diverge on shared outputs suggest a Level 3 semantic problem. A surge in interface change requests between vendor teams suggests a Level 4 pragmatic or Level 6 organisational problem. The framework thereby translates engineering-level interoperability failures into the language of project management — schedule variance, rework frequency, and milestone risk — without requiring the PM to possess specialised data engineering expertise (Section 2.5, Phase 2). Phase 3 solves the response precision problem. In conventional risk management, a failed integration test would be classified under a broad category such as "technical risk," and the PM would assign an engineer to investigate on an ad hoc basis. The PDT framework replaces this with structured, level-specific response logic. A Level 1 technical failure triggers a protocol compatibility audit. A Level 2 syntactic failure triggers middleware reconfiguration. A Level 3 semantic failure triggers an ontological alignment session between domain teams — because the problem is a definitional inconsistency that debugging alone cannot resolve. A Level 4 pragmatic failure triggers workflow redesign. A Level 5 dynamic failure triggers an architecture review of real-time synchronisation mechanisms. A Level 6 organisational failure triggers escalation to senior management for governance realignment. This prevents the PM from spending weeks on code-level debugging when the actual root cause is a semantic convention mismatch, or from convening technical workshops when the problem is a governance misalignment that only contractual intervention can resolve (Section 2.5, Phase 3). By connecting the detected symptom (Phase 2) to a classified root cause (Phase 3) through the pre-structured RBS (Phase 1), the framework ensures each interoperability failure is met with the response category most likely to resolve it — reducing diagnostic delay, minimising misdirected corrective effort, and containing downstream impact on project schedule and cost. This is the operational contribution of the PDT as it transforms interoperability risk from an invisible, after-the-fact discovery into a structured, anticipatable, and level-specifically-addressable project management concern.

4.4 Proposed framework

The fundamental challenge that this framework responds to is structural rather than technical. In multi-stakeholder DT projects such as the EV BHMS, interoperability failures do not arise from any single team's incompetence — they arise because the data handoffs between teams are ungoverned (Darbari, 2024; Naseri et al., 2023; Singh et al., 2021). Four stakeholder groups develop subsystems in parallel using incompatible tool ecosystems (COMSOL, embedded C firmware, Azure/AWS, Teamcenter), with no shared industry standard governing how their outputs should be structured, labelled, or exchanged (Acharya et al., 2024, p.6). These incompatibilities remain invisible during parallel development because each team validates only within its own domain boundary. They surface simultaneously at system integration — the single point in the project lifecycle where schedule float has already been consumed and corrective action carries the highest cost (Cooper et al., 2005, pp.30,49; Raydugin, 2013, p.100).

Existing literature has addressed the diagnostic dimension of this problem. Acharya et al. (2024) classified 77 interoperability challenges across six hierarchical levels — technical, syntactic, semantic, pragmatic, dynamic, and organisational — providing a comprehensive taxonomy of what can go wrong. However, as the thesis identifies, their framework does not translate these challenges into the language of project management. It does not tell a project manager where in the project structure these failures will cause damage, through which dependency pathways they will propagate, who bears responsibility for resolution, or what type of corrective action each failure category demands. The taxonomy remains diagnostic rather than operational.

The proposed framework closes this gap by converting the Acharya et al. taxonomy from a classification scheme into a project-level management instrument. It achieves this through the sequential integration of three established project management tools — WBS, DSM, and RBS — each performing a distinct and non-substitutable function within a three-phase mechanism that spans the project lifecycle.

The WBS establishes administrative ownership by decomposing the BHMS project scope into 19 discrete tasks across five stakeholder groups (Goetsch, 2015, p.68; PMI, 2017, p.412). In a multi-stakeholder DT project, this decomposition is not merely administrative — the WBS boundaries correspond directly to the organisational interfaces where interoperability failures will emerge, because the architecture of the project's organisational structure mirrors the architecture of the technical system being built (Grieves Vickers, 2017, p.108; Eppinger Browning, 2012). Every work package involving a data exchange across these boundaries is systematically screened against the six interoperability levels and flagged as an interoperability-exposed interface. This screening transforms the WBS from a static scope document into an anticipatory risk map.

The DSM addresses what the WBS cannot — lateral dependencies. While the WBS defines who owns each piece of work, it does not model the information flows that cross these ownership boundaries (Gálvez et al., 2015, p.72). The 19×19 process architecture DSM constructed for the BHMS case reveals 29 total information dependencies, of which 12 cross stakeholder group boundaries. Critically, all seven feedback marks — representing coupled tasks where iterative rework is expected — are cross-boundary dependencies. Three distinct dependency loops are identified, each spanning multiple stakeholder groups. These loops establish, in advance, the propagation pathways that an interoperability failure at any flagged interface would follow through the project plan. Without this mapping, a project manager discovering a failure at integration has no structured means of determining which upstream cause produced it or which downstream tasks have been compromised.

The RBS provides the diagnostic precision that generic risk categorisation cannot. In conventional project risk management, interoperability failures would be classified under broad categories such as ”technical risk” (PMI, 2017) or ”internal/technical” (Goetsch, 2015, p.119), producing a single undifferentiated category that obscures the distinction between fundamentally different failure types. The framework replaces this with a six-level classification grounded in the Acharya et al. taxonomy, where each level corresponds to a distinct root cause and therefore demands a distinct response. A syntactic failure — where two systems cannot parse each other’s data formats — requires middleware reconfiguration or format adapter deployment. A semantic failure — where systems parse data correctly but interpret shared variables using different measurement conventions — requires an ontological alignment session between domain teams, because the problem is definitional rather than computational. An organisational failure — where governance structures between vendor companies are misaligned — requires contractual or managerial intervention that no amount of technical debugging can resolve. This level-specific response logic prevents the misallocation of corrective effort that occurs when structurally different failures are treated as a single risk category.

The three-phase mechanism operationalises these instruments across the project lifecycle. During planning, the WBS screening, DSM mapping, and RBS classification are performed together to produce a pre-configured project information architecture — one that recognises interoperability risk before any subsystem is deployed. During execution, five categories of project-level indicators serve as monitoring signals, each linked back through the RBS structure to specific interoperability levels. The project manager monitors these indicators using standard project management instruments — schedule variance, deliverable acceptance rates, interface change request frequency — without requiring specialised data engineering expertise. The framework thereby translates engineering-level interoperability failures into project management language. When an indicator exceeds a pre-defined threshold, the RBS classification of the flagged interface determines the response pathway, ensuring that each failure type is met with the corrective action most likely to resolve it.

The framework's contribution is therefore not the identification of new risks — the Acharya et al. taxonomy already provides that — but the structured translation of those risks into a form that is anticipatable during planning, detectable during execution, and addressable through level-specific responses. It bridges the gap between the information systems literature, which understands interoperability as a socio-technical phenomenon (Acharya et al., 2024; Moser & Grossmann, 2023), and the project management literature, which provides the process architecture and control instruments needed to act on that understanding (Bissonette, 2016; Cooper et al., 2005; PMI, 2017). The framework does not eliminate interoperability failures — it makes them governable.

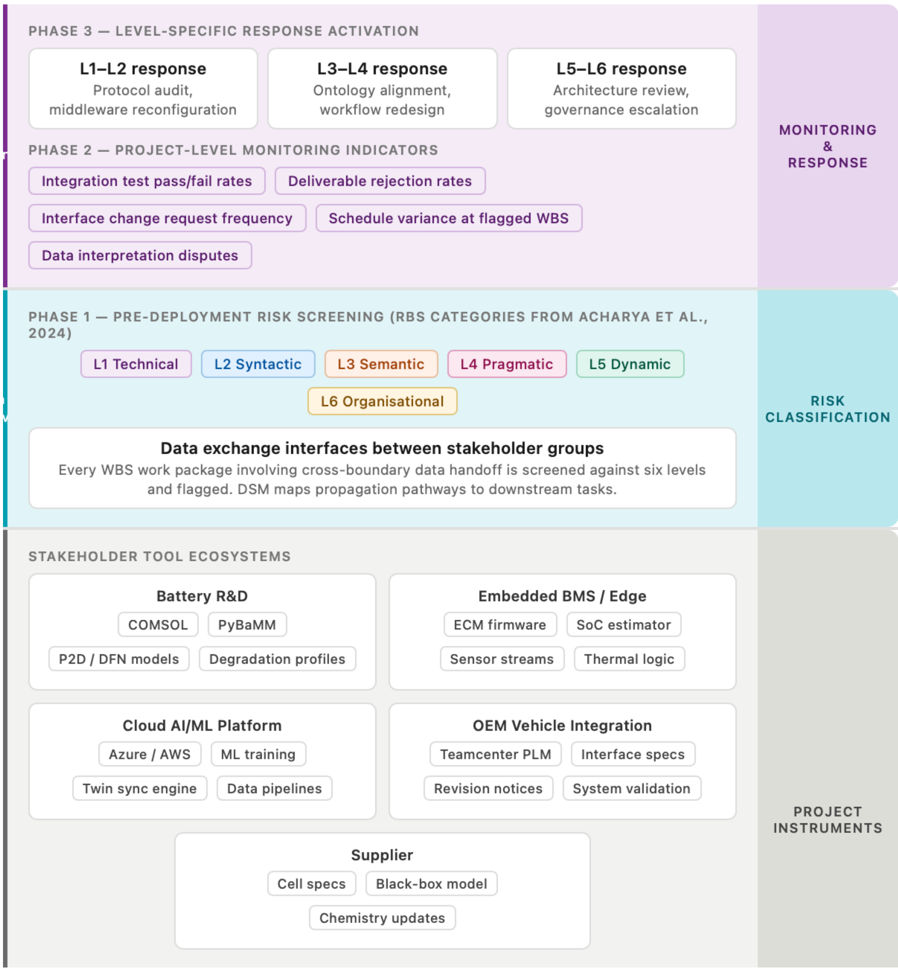

Figure 4.5. Illustration of proposed framework for Project risk monitoring & Control (Picture slightly modified through prompt in claude for visual representation).

Chapter 5

Findings

This chapter presents the results of the case analysis structured around the two research questions and three research objectives defined in Table 1.1. This chapter is organised in two distinct layers: Section 5.1 presents the findings (what was discovered through the WBS, DSM, and RBS analysis), while Section 5.2 presents the interpretation (what these findings mean for project risk management in DT-enabled BHMS projects). All the findings were discovered from the conceptual case study described in Chapter 4.

5.1 Findings for RQ1 / Objectives 1 and 2

5.1.1 Finding 1

Six interoperability failure types were identified at specific stakeholder boundaries. The systematic screening of all data-exchange interfaces in the BHMS case against the Acharya et al. (2024) six-level taxonomy produced the classification summarised in Table 5.1 below. The analysis identified failures at all six levels,however, it concentrated at three boundaries the electrochemical modeling boundary (Levels 1, 2, 6), the embedded BMS boundary (Levels 1, 2, 4), and the cloud platform boundary (Levels 3, 5, 6).

5.1.2 Finding 2

The WBS decomposition identified 19 discrete tasks across five stakeholder groups, with interoperability exposed interfaces concentrated at cross-boundary work packages. The deliverables-oriented WBS (Table 4.2) decomposed the BHMS development scope into 19 tasks distributed across the Electrochemical Modelling Group, the Embedded BMS Team, the Cloud/AI Platform Team, the OEM Vehicle Integration Team, and a cross-cutting Programme Management function. Every work package involving a data exchange across these group boundaries was flagged as an interoperability-exposed interface. The WBS screening transformed the scope document from a static administrative breakdown into an anticipatory risk map by tagging each flagged interface with its relevant interoperability levels from Table 5.1.

5.1.3 Finding 3

All iterative rework in the BHMS case requires cross-team coordination. The DSM analysis reveals that no feedback loop in the BHMS project is contained within a single stakeholder group. Every instance where a downstream task generates information that forces rework on a prior task crosses at least one organisational boundary. This means that whenever iterative rework occurs in this project, it cannot be resolved by one team working independently it inherently demands coordination between teams that operate in different tool ecosystems, follow different data conventions, and may belong to different organisations. This is the structural condition under which interoperability failures are most likely to remain undetected and most expensive to correct, because the team that discovers the problem is not the team that caused it, and neither team has unilateral authority to resolve it. For the project manager, this finding means that interoperability risk cannot be managed as a localised, team-level concern. Every rework cycle is a cross-boundary event that requires a governance response, not merely a technical fix within a single work package.

5.1.4 Finding 4

The DSM establishes traceable propagation pathways that connect interface failures to downstream impact before integration occurs. Without the DSM mapping, a project manager who discovers a failure at the integration gate has no structured way of determining which upstream interface produced the failure or which downstream tasks have already been compromised by proceeding on invalid assumptions. The DSM changes this by establishing, during planning, the specific pathways through which a failure at any flagged interface would propagate through the project schedule. This means that when a monitoring indicator (Phase 2) signals a problem at a particular interface, the project manager can immediately trace forward to identify which tasks are at risk of rework and trace backward to identify which data exchange is the likely source converting what would otherwise be retrospective forensics into anticipatory risk intelligence. For the research, this finding demonstrates that the DSM performs a function that neither the WBS nor the RBS can perform alone: it makes the lateral dependencies between stakeholder groups explicit and actionable, bridging the gap between knowing where interoperability risk exists (WBS) and knowing what type of failure it is (RBS) with knowing how far the damage will spread through the project plan.

5.1.5 Finding 5

The RBS classified each identified risk against the six-level taxonomy, replacing generic "technical risk" labels with interface specific, level specific entries. The comparative analysis of RBS approaches in the literature (Table 4.3) established that conventional project risk management classifies interoperability failures under broad categories such as "technical risk" (PMI, 2017) or "internal/technical" (Goetsch, 2015). The case analysis replaced these with six distinct categories, each corresponding to a different root cause and therefore demanding a different corrective response. Table 5.1 above documents the specific risk entries produced for each interoperability level.

5.2 Findings for RQ2 / Objective 3: The PDT Framework for Monitoring and Control

5.2.1 Finding 6

The three-phase framework produces a structured linkage from planning through monitoring to response. The framework operates across three sequential phases mapped to the project lifecycle. Table 5.4 summarises what each phase produces, what instruments it uses, and what output it delivers.

5.2.2 Finding 7

Five categories of project-level monitoring indicators were defined, each linked to specific interoperability levels. Phase 2 of the framework identified five observable indicators that a project manager can monitor without requiring specialised data engineering expertise.Table 5.3 maps each indicator to the interoperability level it signals.

5.2.3 Finding 8

The framework produces a level-specific response logic that maps each failure type to a distinct corrective action. Phase 3 of the framework replaces the conventional ad hoc investigation approach with a structured response pathway determined by the RBS classification of the failure's root cause. Table 5.2 summarises the six response pathways.

5.3 Consolidated Findings to Research Question Mapping

Table 5.5 provides a single-page traceability matrix showing how each finding answers the research questions and objectives.

Table 5.1. Summary of Interoperability Failures Identified by Level and Stakeholder Boundary.

Interoperability Level	Boundary Where Identified	Specific Failure Found	Project-Level Risk Translation
Level 1 Technical	Electrochemical ↔ Cloud; Embedded ↔ Cloud	Protocol rejection between vendor-specific APIs; connectivity loss at edge–cloud interface.	**Infrastructure risk**: integration blocked until protocol alignment achieved.
Level 2 Syntactic	Electrochemical ↔ Cloud; Embedded ↔ Cloud	COMSOL/PyBaMM outputs not natively consumable by cloud pipeline; edge sensor streams require custom translation at every handoff.	**Cost risk**: unplanned, recurring translation effort invisible in schedule until surfacing as delay. Each re-parameterisation cycle reproduces the same burden.
Level 3 Semantic	Cloud platform boundary (receiving from modelling + edge)	Same physical quantities (voltage, temperature) carry different measurement conventions across teams; no shared ontology binding the four groups to common definitions.	**Quality risk**: misinterpretation propagates silently into SoC/SoH estimates; not caught by syntactic validation since the data parses correctly.
Level 4 Pragmatic	Embedded BMS boundary	Conflicting operational workflows between edge real-time processing and cloud batch processing.	**Schedule risk**: workflow incompatibility forces redesign of data pipeline handoff procedures.
Level 5 Dynamic	Cloud platform boundary	Synchronisation fails under latency; retraining workflow re-executes on every cell chemistry update with no mechanism ensuring all four teams are on same revision.	**Change-control risk**: silent version drift detectable only at integration; scope and configuration change propagates across all four teams simultaneously.
Level 6 Organisational	Electrochemical ↔ OEM; cross-programme governance	No shared standard; handoffs governed by bilateral negotiation; proprietary OEM platforms deepen governance gap; no cross-team configuration baseline.	**Governance risk**: no monitoring instrument tracks cross-team interface status; failures accumulate invisibly because no single stakeholder owns the interfaces.

Table 5.2. Phase 3 Level-Specific Response Logic..

Failure Level	Corrective Action Triggered	Rationale for Specificity
Level 1 Technical	Infrastructure review and protocol compatibility audit.	Failure is a connectivity or protocol mismatch resolvable through infrastructure reconfiguration.
Level 2 Syntactic	Middleware reconfiguration or data format adapter deployment.	Systems connect but cannot parse each other's data structures.
Level 3 Semantic	Ontological alignment session between domain teams.	Problem is definitional (meaning), not computational; debugging alone cannot resolve it.
Level 4 Pragmatic	Workflow redesign for operational compatibility.	Systems exchange data correctly but use it in incompatible operational ways.
Level 5 Dynamic	Architecture review of real-time synchronisation mechanisms.	Failure occurs in temporal coordination of live data exchange between subsystems.
Level 6 Organisational	Escalation to senior management for governance realignment.	Technology works but human teams, vendor companies, or business structures fail to align; only contractual or managerial intervention resolves it.

Table 5.3. Phase 2 Monitoring Indicators and Their Interoperability Level Linkage..

Monitoring Indicator	What It Signals	Interoperability Level Indicated
Integration test pass/fail rates at tagged interfaces.	Direct evidence of connectivity or format failures at specific interfaces.	Level 1 (technical) or Level 2 (syntactic).
Deliverable rejection rates at interoperability-exposed work packages.	Outputs from one subsystem fail acceptance criteria of the receiving subsystem despite passing individual validation.	Level 3 (semantic).
Frequency of interface specification change requests between vendor teams.	Emerging misalignment in how teams use shared data or govern their interfaces.	Level 4 (pragmatic) or Level 6 (organisational).
Schedule variance in work packages downstream of flagged data exchange points.	Silent propagation of an upstream interoperability failure through the dependency chain mapped in the DSM.	Any level; propagation pathway identified via DSM.
Unresolved data interpretation disputes escalated during design reviews.	Domain teams disagree on meaning of shared variables or measurement conventions.	Level 3 (semantic).

Table 5.4. Three-Phase PDT Framework: Outputs by Phase.

Phase	Problem Addressed	Instruments Used	Output Produced
Phase 1: Pre-deployment Risk Structuring	Visibility problem: interoperability risks are invisible during parallel development and discoverable only at the integration gate.	WBS screening against 6-level taxonomy; DSM dependency mapping; RBS level-specific classification.	Pre-configured project information architecture: WBS with tagged interfaces, RBS with level-specific entries, DSM with mapped impact pathways.
Phase 2: Execution-Phase Monitoring	Translation problem: engineering-level failures are not observable in project management language.	Five categories of project-level monitoring indicators (see Table 5.5).	Continuous detection of interoperability failures through observable project-level symptoms, each linked to specific interoperability levels via the RBS.
Phase 3: Response Activation	Precision problem: generic “technical risk” responses lead to misallocated corrective effort.	RBS classification of root cause; level-specific response logic.	Targeted corrective action matched to the failure type rather than ad hoc investigation.

Table 5.5. Traceability Matrix: Findings → Research Questions → Research Objectives..

Finding	What Was Discovered	Answers RQ	Fulfils Objective	Instrument / Evidence
F1	Six interoperability failure types identified at specific stakeholder boundaries.	RQ1	Obj. 1	WBS screening + Acharya et al. (2024) taxonomy.
F2	19 tasks across 5 stakeholder groups; interoperability-exposed interfaces tagged at cross-boundary work packages.	RQ1	Obj. 2	WBS (Table 4.2).
F3	All iterative rework requires cross-team coordination; no feedback loop is contained within a single stakeholder group.	RQ1	Obj. 2	DSM (Figure 4.4).
F4	Traceable propagation pathways connect interface failures to downstream impact before integration occurs.	RQ1	Obj. 2	DSM feedback analysis.
F5	RBS replaces generic "technical risk" labels with six-level, interface-specific risk entries.	RQ1	Obj. 2	RBS (Table 4.3 + case analysis).
F6	Three-phase framework links planning → monitoring → response across the project lifecycle.	RQ2	Obj. 3	Framework design (Figure 4.5).
F7	Five project-manager-observable monitoring indicators defined, each linked to specific interoperability levels.	RQ2	Obj. 3	Phase 2 design (Table 5.5).
F8	Six level-specific response pathways replace ad hoc investigation with structured corrective logic.	RQ2	Obj. 3	Phase 3 design (Table 5.6).

Chapter 6

Interpretation of Results

This chapter discusses what the findings presented in Section 5.1 mean. The interpretation is separated from the findings to maintain analytical clarity and to distinguish between what the analysis produced and what the researcher concludes from those outputs.

6.1 Answering RQ1: From Interoperability Challenges to Project-Level Risks

The combined WBS–DSM–RBS analysis demonstrates that data interoperability challenges in DT-based BMS development can be systematically identified and translated into project-level risks through a three-instrument decomposition. The key interpretive conclusions are as follows. First, interoperability risk in this case is not a single category but a structured family of six distinct failure types, each with a different root cause and a different project-level consequence. The analysis shows that treating interoperability as a monolithic "technical risk" — as conventional PRM frameworks do — obscures the distinction between failures that require middleware fixes (Level 2) and failures that require governance intervention (Level 6). The practical consequence of this finding is that corrective effort risks being systematically misallocated if the risk classification does not distinguish between these levels. Second, the DSM analysis reveals that every feedback loop in the BHMS case crosses at least one stakeholder boundary. No rework circuit is contained within a single team. This means that every iterative rework cycle in this project requires cross-team coordination — precisely the condition under which interoperability failures are most costly and most likely to remain undetected. The concentration of all seven feedback marks at cross-boundary interfaces confirms the theoretical expectation that the project's organisational structure mirrors its technical architecture, and that the organisational seams are where interoperability risk materialises. Third, the three rework circuits identified in the DSM provide, for the first time in this case, traceable propagation pathways that connect a failure at a specific interface to the downstream tasks it will affect. Without this mapping, a project manager discovering a failure at integration would have no structured means of determining which upstream cause produced it or which downstream tasks have been compromised. The DSM converts what would otherwise be retrospective forensics into anticipatory risk intelligence.

6.1.1 Answering RQ2: The PDT as a Risk Monitoring and Control Instrument

The three-phase framework demonstrates how a Project Digital Twin can support interoperability risk monitoring and control by solving three sequential problems: visibility (Phase 1), translation (Phase 2), and precision (Phase 3). The contribution is that Phase 1 reverses the conventional sequence, instead of discovering interoperability risks at the integration gate that is the point of maximum cost and minimum schedule float; the framework rather structures these risks during planning, before any subsystem is deployed. The WBS screening, DSM mapping, and RBS classification together produce a pre-configured project information architecture that recognise interoperability risk proactively. The translation contribution is that Phase 2 converts engineering-level interoperability failures into the language of project management. The five monitoring indicators (Table 5.5) are observable through standard PM instruments such as schedule variance, deliverable acceptance rates, interface change request frequency and do not require the project manager to possess specialised data engineering expertise. This addresses a practical barrier: in most multi-stakeholder DT projects, the PM cannot and should not monitor the DT's internal data streams directly; Phase 2 defines what the PM should monitor instead. The precision contribution is that Phase 3 replaces the conventional ad hoc response with level-specific corrective logic. The practical significance is best illustrated by contrast: without level-specific classification, a PM encountering a failed integration test might spend weeks on code-level debugging when the actual root cause is a semantic convention mismatch (Level 3) that requires an ontological alignment session, or might convene technical workshops when the actual problem is a governance misalignment (Level 6) that only contractual intervention can resolve. The framework's level specific response logic (Table 5.6) prevents this misallocation.

6.2 Limitations of the Results

The results are subject to the methodological limitations acknowledged in Chapter 3. The framework is conceptual and has not been validated in a live project environment. The interoperability failures identified in Table 5.1 were derived from published literature and industry documentation, not from primary data collection within an active BHMS project. The monitoring indicators in Table 5.5 are proposed on the basis of analytical logic; their sensitivity and reliability in detecting actual interoperability failures in real time have not been empirically tested. The rework circuits in Table 5.3 represent structurally plausible propagation pathways, but their actual cost and schedule impact in a specific project instance would depend on variables (team capacity, buffer allocation, contractual arrangements) that a conceptual study cannot capture. These limitations define the boundary between the design science phases this thesis covers (Phases 1–3) and the empirical testing phase (Phase 4) that remains for future research.

6.3 Conclusion

This chapter concludes the discussion by presenting eight distinct findings derived from the WBS, DSM, and RBS analysis of the EV BHMS case study. Findings 1–5 answer RQ1 by demonstrating how interoperability challenges can be identified at specific stakeholder boundaries and translated into structured, level-specific project-level risks. Findings 6–8 answer RQ2 by showing how the three-phase PDT framework supports monitoring and control through pre-deployment risk structuring, project-level indicator monitoring, and level-specific response activation. The findings and their interpretations have been presented separately throughout this chapter: Section 5.1 reports what the analysis produced, while Section 5.2 discusses what these outputs mean for project risk management practice. The traceability matrix (Table 5.7) provides a consolidated mapping from each finding to its corresponding research question, objective, and analytical instrument.

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