

## **STEEPLEM Strategic Foresight for Industrial Metaverse Technologies in Maintenance Support and Technician Skill Development**

**James U. Okoroama**

Industrial Practitioner & Independent Researcher, MindCraft Synergy Consulting, United States

Corresponding author: James U. Okoroama, [james@mcssynergy.com](mailto:james@mcssynergy.com)

### **Abstract**

An industrial metaverse that fuses artificial intelligence, robotics, digital twins and extended reality could change how maintenance is performed and how technicians are trained, but its development depends on interacting social, technological, economic, environmental, political, legal, ethical and media forces. This conceptual paper applies a STEEPLEM foresight analysis to the use of industrial metaverse technologies for maintenance support and skill development. The force scores are the author's structured judgments, informed by the literature, and are reported transparently so that readers can substitute their own. On these scores, technology adoption and the intensity of regulation emerge as critical uncertainties, a selection supported in 98.5 percent of 10,000 perturbed draws when correlated forces are grouped into adoption and regulation clusters. Four scenarios are constructed on these axes, and six emergent patterns and nine future logics are traced. A minimax regret analysis of six strategic moves, repeated under four value scales, ranks tacit knowledge capture as the only move without regret in any scenario within the assigned payoff matrix, while proprietary platform lock-in carries the highest regret. Because the payoffs are ordinal judgments, these rankings indicate robustness under stated assumptions rather than universal superiority. The paper offers a transparent, reproducible approach to strategy under deep uncertainty and five propositions for testing how industrial technologies are adopted.

**Keywords:** Industrial metaverse; strategic foresight; scenario planning; STEEPLEM analysis; digital twin; Industry 4.0; artificial intelligence governance

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### **1. Introduction**

Industrial and advanced manufacturing sectors worldwide are experiencing rising sophistication driven by the fusion of emerging technologies. Robotics and autonomous systems, the internet of

everything, virtual and augmented reality, machine learning and generative artificial intelligence are being combined in Industry 4.0 operations in ways that were not feasible a decade ago (Lasi et al., 2014; Xu et al., 2021). Digital twins, which maintain synchronized virtual representations of physical assets, provide the connective tissue for much of this integration, linking sensor data, simulation and decision support (Tao et al., 2019). Extended reality allows people to see and manipulate these virtual representations in the context of physical equipment (Masood and Egger, 2019). The combination of these capabilities in shared, persistent, interactive environments is increasingly described as an industrial metaverse (Dwivedi et al., 2022; Mystakidis, 2022).

For maintenance and advanced manufacturing, the industrial metaverse promises several benefits. Digital twins can give artificial intelligence models access to a vast array of operational data, allowing them to augment automation expertise with clear explanations, expert guidance and efficient troubleshooting. The same data can train new entrants on real-life scenarios of the challenges they will encounter, closing skills gaps that conventional apprenticeship cannot close quickly enough. Predictive and prescriptive maintenance can draw on simulated failure trajectories as well as historical data. Remote experts can collaborate with on-site technicians inside a shared virtual model of the equipment (Palmarini et al., 2018). These benefits make the industrial metaverse an issue-stroke-opportunity: a source of both disruption and advantage for the organizations that operate complex automated assets.

Yet the path from promise to practice is uncertain. Costs are high and returns are unevenly distributed. The current generation of experienced professionals is often wary of new technology even while working with it daily, and new entrants, though digitally fluent, are less interested in traditional routes to skill acquisition. Governments are moving to regulate artificial intelligence and data use, with the European Union adopting a comprehensive artificial intelligence regulation in 2024 (European Union, 2024). Ethical concerns about bias, transparency and job displacement shape public and workforce attitudes (Floridi et al., 2018). Sustainability pressures push in favor of resource-efficient digital operations but also raise questions about the energy footprint of computing. Decision-makers therefore face deep uncertainty about how fast and in what form the industrial metaverse will develop.

Strategic foresight offers tools for exactly this kind of problem. Rather than predicting a single future, foresight methods identify the forces that shape the future, distinguish predetermined elements from critical uncertainties and construct plausible scenarios against which strategies can be tested (Schoemaker, 1995; Wack, 1985). Environmental scanning frameworks organize the forces into categories so that no major domain is overlooked (Aguilar, 1967). Corporate foresight has been associated with superior firm performance when it is systematically embedded in strategy processes (Rohrbeck and Kum, 2018). Scenario-based modelling is also increasingly used to support long-term organizational planning under uncertainty (Filani et al., 2023).

This paper applies these tools to the industrial metaverse for maintenance and advanced manufacturing. It asks which forces will dominate the development of an industrial metaverse that fuses artificial intelligence, robotics, machine learning, digital twins and augmented reality; what future logics and emergent patterns arise from their interaction; and how organizations should triage these forces to set strategic direction. The paper makes four contributions. It provides a structured STEEPLM assessment of the industrial metaverse with explicit impact and uncertainty scores. It constructs four scenarios around the two critical uncertainties of technology adoption and regulation. It identifies emergent patterns and nine future logics. And it proposes a triage framework with no-regret moves that remain valuable across scenarios. Section 2 reviews the literature, Section 3 explains the method, Section 4 presents the force analysis, Section 5 the scenarios, Section 6 the emergent patterns, Section 7 the triage framework and strategic direction, Section 8 the discussion, and Section 9 concludes.

The paper addresses three research questions. RQ1 asks which STEEPLM forces will dominate the development of an industrial metaverse for maintenance and advanced manufacturing, and how robust that judgment is to scoring uncertainty. RQ2 asks what scenarios and emergent patterns arise from the interaction of the critical uncertainties. RQ3 asks which strategic moves remain valuable across scenarios and how organizations should triage the forces they face. These questions follow the sequence of trend identification, uncertainty selection and strategy testing that characterizes scenario-based strategy (Schoemaker, 1995).

## **2. Literature Review**

### ***2.1 The Industrial Metaverse and Its Enabling Technologies***

The metaverse concept originated in consumer computing as a persistent, shared virtual space, but its industrial variant emphasizes the coupling of virtual environments with physical production systems. Mystakidis (2022) defined the metaverse as a post-reality universe that merges physical reality with digital virtuality through extended reality and multi-user interaction. Dwivedi et al. (2022) brought together multidisciplinary perspectives on the metaverse and identified industrial and educational applications among its most promising uses, while warning of significant technical, social and governance challenges. In industrial settings, the metaverse builds on the cyber-physical systems architecture of Industry 4.0, in which physical assets are connected to computational models through layers of data acquisition, analysis and configuration (Lee et al., 2015). Asset lifecycle management with inventory visibility (Okonkwo et al., 2023b) and automation with digital twins to reduce procurement errors (Akinlade et al., 2024) show how virtual models are extending into the supply side of industrial operations. In this paper, the industrial metaverse is distinguished from three related technologies. A connected digital twin is a synchronized model of an asset; remote assistance connects a field technician to an expert through video or augmented reality; and immersive training places a learner in a virtual environment. The industrial metaverse, as used here, refers to the integration of these elements into persistent, shared environments in which multiple people and intelligent agents interact with synchronized models of real operations, so that the same virtual space supports monitoring, collaboration and learning (Dwivedi et al., 2022).

Digital twins are central to this architecture. Grieves and Vickers (2017) described the digital twin as a virtual representation that mirrors a physical system throughout its lifecycle, enabling prediction and mitigation of undesirable emergent behavior. Kritzinger et al. (2018) distinguished digital models, digital shadows and digital twins according to the degree of automatic data integration between physical and virtual objects. Tao et al. (2019) reviewed digital twin applications in industry and found growing use in design, production, prognostics and health management. Ivanov and Dolgui (2021) extended the concept to supply chains, showing how a digital supply chain twin can support disruption risk management. Data-driven

digital transformation models for lifecycle performance management in infrastructure delivery reflect the same direction of travel (Adelanwa et al., 2023).

Extended reality supplies the human interface. Palmarini et al. (2018) reviewed augmented reality applications in maintenance and found benefits in guidance, training and remote assistance, along with limitations in hardware ergonomics and content authoring. Masood and Egger (2019) identified organizational and technical success factors for augmented reality in Industry 4.0, including fit with work processes and user acceptance. Artificial intelligence provides the analytic engine, from predictive maintenance models to generative assistants. Autonomous mobile robots and path-planning algorithms extend the metaverse into material movement, where virtual models are used to optimize physical flows (Akanbi and Sunday, 2024). Industry 5.0 thinking adds a human-centric emphasis, arguing that technology should augment rather than replace human workers and should serve sustainability and resilience goals (Nahavandi, 2019; Xu et al., 2021).

## **2.2 Strategic Foresight and Environmental Scanning**

Environmental scanning frameworks help organizations monitor the external forces that shape their strategic options. Aguilar (1967) introduced systematic scanning of the business environment, and later frameworks such as PEST, PESTEL and STEEPLE organized forces into political, economic, social, technological, environmental, legal and ethical categories. The STEEPLM variant used in this paper adds a media dimension, recognizing that public narratives and media coverage influence technology acceptance, regulation and investment. These frameworks are most useful when they are not merely checklists but feed into structured assessment of impact and uncertainty. Real-time KPI tracking systems provide the monitoring layer through which foresight signposts can be observed (Schoemaker, 1995), and predictive schedule-risk methods for hyperscale AI data centers show how forward-looking analytics are being applied to the infrastructure on which the industrial metaverse depends (Zhou et al., 2024).

Scenario planning builds on scanning by constructing alternative futures. Wack (1985) described how scenarios helped Royal Dutch Shell anticipate the 1970s oil shocks by changing managers' mental models rather than predicting events. Schoemaker (1995) set out a practical method for scenario construction that identifies trends and key uncertainties, selects the two most important

uncertainties as axes, and develops internally consistent scenarios in each quadrant. Bradfield et al. (2005) traced the evolution of scenario techniques and distinguished intuitive logics, probabilistic modified trends and prospective approaches. Amer et al. (2013) reviewed scenario planning literature and highlighted the value of combining qualitative and quantitative methods. Ramírez and Wilkinson (2016) emphasized scenarios as tools for reframing strategic situations rather than forecasting.

Foresight has been shown to matter for performance. Rohrbeck and Kum (2018) found that firms with mature corporate foresight achieved higher profitability and market capitalization growth than less prepared firms. In technology-intensive sectors, foresight helps organizations avoid both premature commitment to immature technologies and late adoption of transformative ones. Sustainable business models for large service organizations increasingly rely on predictive and strategic insight to balance these risks (Nnabueze et al., 2023), and digital transformation programs that combine automation with explicit risk reduction tend to deliver more durable commercial efficiency (Sakyi et al., 2024b).

### ***2.3 Technology Adoption, Workforce and Social Acceptance***

The adoption of industrial metaverse technologies depends on organizational and individual acceptance. The technology acceptance model and its successors identify perceived usefulness, ease of use, social influence and facilitating conditions as determinants of adoption (Davis, 1989; Venkatesh et al., 2003). Diffusion of innovations theory adds that relative advantage, compatibility, complexity, trialability and observability shape the rate of adoption across populations (Rogers, 2003). Employee readiness frameworks emphasize that technology adoption succeeds when organizations deliberately build the skills and confidence of their workforce (Akhigbe et al., 2024), and assessments of artificial intelligence readiness in smaller enterprises highlight skills and cost as persistent barriers (Alieme et al., 2023). Adoption also depends on how organizations integrate IT systems engineering with operations (Okonkwo et al., 2023a). Skills-mapping analyses of just transitions show that technology change redistributes work and requires deliberate reskilling (Komi and Adamolekun, 2024).

The workforce effects of automation are contested. Frey and Osborne (2017) estimated that a large share of occupations were susceptible to computerization, while Acemoglu and Restrepo

(2020) found measurable negative effects of industrial robots on employment and wages in exposed local labor markets. Brynjolfsson and McAfee (2014) argued that digital technologies create both abundance and dislocation, and that outcomes depend on how institutions and skills adapt. Sony and Naik (2020) argued from socio-technical systems theory that Industry 4.0 outcomes depend on joint optimization of technology and social systems. In maintenance, the specific challenge is the coexistence of an aging, highly skilled workforce with deep equipment knowledge and a younger, digitally fluent workforce that lacks that knowledge. Strategies for bridging the digital divide in technical education provide one route to addressing this imbalance (Joseph and Uzundu, 2024a).

#### **2.4 Regulation, Ethics and Governance of Industrial Artificial Intelligence**

Regulation of artificial intelligence and data has advanced rapidly. The European Union adopted a risk-based regulation that classifies artificial intelligence systems by risk level and imposes obligations on high-risk applications, including those used as safety components of machinery (European Union, 2024). In the United States, NIST published an artificial intelligence risk management framework that organizes trustworthy artificial intelligence practices around governance, mapping, measurement and management (National Institute of Standards and Technology [NIST], 2023). Compliance requires organizations to classify their artificial intelligence systems, maintain risk management and technical documentation and provide human oversight for high-risk applications (European Union, 2024), which demands governance capabilities that many industrial firms are still building, and harmonizing data protection obligations across jurisdictions remains a significant compliance challenge (Ominyi and Anichukwueze, 2022a). Privacy by design has been proposed as a structural requirement for corporate restructuring and data-intensive transactions (Ominyi, 2021) and standardizing previously unstandardized compliance controls reduces regulatory uncertainty (Uchechi et al., 2023). The harmonization of digital trade regulations (Jones and Ominyi, 2024) bears directly on platforms that cross borders.

Ethical concerns shape both regulation and acceptance. Jobin et al. (2019) mapped global artificial intelligence ethics guidelines and found convergence around transparency, justice and fairness, non-maleficence, responsibility and privacy. Floridi et al. (2018) proposed an ethical

framework built on beneficence, non-maleficence, autonomy, justice and explicability. Mehrabi et al. (2021) surveyed sources of bias in machine learning and showed how biased data and design choices can produce unfair outcomes. In industrial settings, bias may appear as maintenance models that perform poorly on underrepresented equipment types or as workforce analytics that disadvantage certain groups. Algorithmic accountability and model risk management practices developed in financial services offer transferable governance tools (Ominyi and Anichukwueze, 2023; Annan, 2024), and responsible artificial intelligence governance structures for automated decision systems in regulated industries are maturing (Ominyi and Anichukwueze, 2024).

The pace of technological change also challenges regulators. Collingridge (1980) described the dilemma that technologies are easiest to control when their effects are least understood, and hardest to control once their effects become clear. Marchant et al. (2011) termed the growing gap between emerging technologies and legal-ethical oversight the pacing problem. For the industrial metaverse, regulatory lag creates uncertainty about liability, data ownership and safety certification. Questions of intellectual property ownership in artificial intelligence-generated content (Annan, 2023) and data privacy governance for cross-border digital platforms (Annan, 2022) are directly relevant where digital twins and training content are shared across sites and suppliers.

### **2.5 Economic and Environmental Dimensions**

The economic case for Industry 4.0 rests on productivity, quality and flexibility gains, but the investment is substantial and benefits accrue unevenly. Kagermann et al. (2013) set out the German strategic initiative for Industrie 4.0 and emphasized the need for standardization, workforce development and supportive regulation. Müller et al. (2018) found that implementation is driven by strategic, operational and environmental opportunities but held back by competitiveness and future viability concerns and by organizational and production fit. Small and medium-sized enterprises face particular barriers of cost and capability, which risks widening gaps between large and small firms. Public-private partnerships and supplier relationship management that foster collaboration and resilience can lower these barriers (Ike et al., 2021). Green bonds and ESG-linked financing are reshaping the economics of technology

investment (Sakyi et al., 2024a), ESG adoption within smaller supply chains can be evaluated quantitatively (Akinleye, 2023) and greenhouse gas disclosure obligations are tightening for energy and infrastructure enterprises (Ominyi and Anichukwueze, 2022b). Large-scale renewable integration strategy (Yeboah and Ike, 2020) and smart grid architectures for high renewable penetration (Adenuga, 2022) shape the energy context in which computing-intensive platforms will operate. In many regions, access to reliable electricity remains a precondition for digital infrastructure, as assessments of solar-based electronic systems for rural electrification illustrate (Ejimah and Aregbe, 2020).

Environmental considerations increasingly influence technology decisions. Stock and Seliger (2016) identified opportunities for sustainable manufacturing in Industry 4.0 through resource-efficient production and closed-loop value chains. Kiel et al. (2017) found that industrial value creation through Industry 4.0 can deliver environmental as well as economic benefits. Geissdoerfer et al. (2017) described the circular economy as a sustainability paradigm that relies on design for reuse, repair and recycling, all of which digital twins can support by modelling lifecycle impacts. Integrating artificial intelligence with environmental, social and governance metrics is increasingly used to audit smart infrastructure (Okojie et al., 2023), while analyses of large-scale renewable energy integration show that energy transitions carry economic and social as well as environmental consequences (Joseph and Uzundu, 2024b). Data center lifecycle management has become a material environmental and security concern as computing loads grow (Amayo et al., 2024a).

## ***2.6 Positioning Against Existing Foresight Approaches***

Table 1 positions this study against established foresight and Industry 4.0 strategy approaches on five dimensions: a focus on industrial maintenance and advanced manufacturing, quantified impact and uncertainty scores, an explicit scenario set, analysis of the interaction between workforce and regulation, and translation into triage and no-regret actions. Environmental scanning offers comprehensive categories but not scenarios (Aguilar, 1967); intuitive logics scenario planning offers scenarios but not domain content (Schoemaker, 1995; Wack, 1985); corporate foresight research links foresight to performance but is not industry-specific (Rohrbeck and Kum, 2018); the metaverse research agenda is broad and multidisciplinary (Dwivedi et al.,

2022); and the Industrie 4.0 recommendations focus on implementation rather than uncertainty (Kagermann et al., 2013).

**Table 1.** Comparison of foresight and Industry 4.0 strategy approaches with this study across five dimensions

| Approach                                     | Industrial maintenance focus | Quantified impact and uncertainty | Explicit scenario set | Workforce and regulation interaction | Triage and no-regret actions |
|----------------------------------------------|------------------------------|-----------------------------------|-----------------------|--------------------------------------|------------------------------|
| Environmental scanning                       | No                           | No                                | No                    | No                                   | No                           |
| Intuitive logics scenario planning           | No                           | Partial                           | Yes                   | No                                   | Partial                      |
| Corporate foresight maturity research        | No                           | No                                | Partial               | No                                   | Partial                      |
| Metaverse research agenda                    | Partial                      | No                                | No                    | Partial                              | No                           |
| Industrie 4.0 implementation recommendations | Partial                      | No                                | No                    | Partial                              | Partial                      |
| This study                                   | Yes                          | Yes                               | Yes                   | Yes                                  | Yes                          |

## 2.7 Research Gap

Existing research describes the enabling technologies of the industrial metaverse, the methods of strategic foresight and the governance challenges of industrial artificial intelligence, but it has rarely brought them together. Studies of digital twins and extended reality focus on technical feasibility and use cases (Tao et al., 2019; Palmarini et al., 2018). Studies of the metaverse take a broad multidisciplinary view that is not specific to maintenance and manufacturing (Dwivedi et al., 2022). Foresight studies of Industry 4.0 seldom address the specific interaction of workforce dynamics and regulation that this paper identifies as decisive. There is therefore a need for a structured foresight analysis that scores the forces shaping the industrial metaverse, constructs scenarios around its critical uncertainties and translates them into strategic direction for maintenance and manufacturing organizations.

## 3. Methodology

The study uses an intuitive logics approach to scenario planning, combined with a quantitative scoring of forces. Intuitive logics scenarios are developed through structured reasoning about the drivers of change and their interactions, and they are the most widely used scenario method in

corporate strategy (Bradfield et al., 2005). The process followed the steps described by Schoemaker (1995): defining the scope and time frame, identifying the major forces, distinguishing trends from uncertainties, selecting the critical uncertainties, constructing scenarios, and deriving strategic implications.

The scope is the development of an industrial metaverse that fuses artificial intelligence, robotics, machine learning, digital twins and augmented reality for industrial maintenance, advanced manufacturing and prescriptive maintenance reliability, together with associated skill development. The time frame is the decade from 2024 to 2034. Forces were identified through an integrative literature review across technology, management, labor economics, regulation and ethics (Torraco, 2005; Snyder, 2019) and organized under the eight STEEPLM categories. The first author's practical experience leading reliability engineering, robotics and facilities maintenance in automated operations informed the assessment of how each force manifests on the shop floor.

Each force was scored on a ten-point scale for impact, meaning the magnitude of its effect on the development of the industrial metaverse, and for uncertainty, meaning the degree to which its direction and magnitude are unknown. Scores were assigned through structured expert judgment informed by the literature, a common approach in scenario planning where data on future developments are by definition unavailable (Amer et al., 2013). The scores are therefore interpretive rather than statistical, and they are reported transparently so that readers can test alternative judgments. The two forces combining the highest impact and uncertainty were selected as scenario axes. Emergent patterns were derived by examining pairwise interactions between forces, and the triage framework and future logics were derived from the scenarios using the no-regret and robustness principles of scenario-based strategy (Ramírez and Wilkinson, 2016).

The study is a conceptual and foresight article rather than a systematic review (Jaakkola, 2020). Its literature base was selected purposively to cover each STEEPLM domain, drawing on foundational foresight, technology and governance works and on applied studies from a curated practitioner-research bibliography retained only where they bore on a specific force. Following Webster and Watson (2002), sources were coded to the force or scenario element they inform, as

mapped in Table 2. All impact and uncertainty scores were assigned by the author as structured expert judgment; no external panel was convened, and the scores are therefore presented as transparent, contestable inputs rather than as measured quantities. The scope is restricted to maintenance support and technician skill development, which narrows the forces to those most relevant to these applications.

**Table 2.** Evidence map linking analysis elements to the sources that inform them

| <b>Analysis element</b>           | <b>Principal conceptual sources</b>                                    | <b>Applied and contextual sources</b>             | <b>Use in the analysis</b>                                   |
|-----------------------------------|------------------------------------------------------------------------|---------------------------------------------------|--------------------------------------------------------------|
| Enabling technologies             | Tao et al. (2019); Grieves and Vickers (2017); Palmarini et al. (2018) | Akanbi and Sunday (2024); Okonkwo et al. (2023b)  | Defines the technical scope of the metaverse for maintenance |
| Foresight method                  | Schoemaker (1995); Wack (1985); Amer et al. (2013)                     | Filani et al. (2023)                              | Structures scoring, axes and scenarios                       |
| Social and workforce forces       | Venkatesh et al. (2003); Rogers (2003); Sony and Naik (2020)           | Akhigbe et al. (2024); Komi and Adamolekun (2024) | Informs social force scores and patterns                     |
| Legal and ethical forces          | European Union (2024); NIST (2023); Floridi et al. (2018)              | Ominyi and Anichukwueze (2024); Annan (2024)      | Informs regulation axis and ethical patterns                 |
| Economic and environmental forces | Müller et al. (2018); Kiel et al. (2017); Geissdoerfer et al. (2017)   | Ike et al. (2021); Okojie et al. (2023)           | Informs economic and environmental scores                    |
| Strategy under uncertainty        | Savage (1951); Walker et al. (2013); Ramírez and Wilkinson (2016)      | Okonkwo et al. (2024a)                            | Supports triage and regret analysis                          |

## 4. STEEPLM Force Analysis

### 4.1 Identification of Forces

Table 3 summarizes the eight STEEPLM forces and the principal ways each affects the development of an industrial metaverse for maintenance and advanced manufacturing. The forces differ in their character: some, such as technological advance, are strongly directional; others, such as regulation, could move in either direction depending on political choices. Organizing the forces in this way follows the environmental scanning tradition, which seeks to ensure that no major domain of external change is overlooked when strategy is formulated (Aguilar, 1967). The forces were identified by applying each STEEPLM category to the specific use of metaverse technologies for maintenance support and skill development, drawing

on the sources mapped in Table 2, and each force is described by its mechanism of influence rather than by a general trend so that its effect on the scenarios can be traced (Aguilar, 1967; Amer et al., 2013).

**Table 3.** STEEPLEM forces shaping the industrial metaverse for maintenance and advanced manufacturing

| Force         | Principal manifestation                                                                                                          | Key question                                                      |
|---------------|----------------------------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------|
| Social        | Aging skilled workforce wary of technology; younger workforce digitally fluent but less drawn to apprenticeship; user acceptance | Will the workforce adopt and be able to use the technologies?     |
| Technological | Advances in AI, ML, robotics, digital twins and AR; cybersecurity of integrated platforms                                        | How capable, reliable and secure will the integrated platform be? |
| Economic      | Cost of implementation; return on investment; competitive pressure; SME access                                                   | Will benefits justify costs, and for whom?                        |
| Environmental | Resource efficiency, emissions reduction, circular models; energy demand of computing                                            | Will the metaverse reduce or add to environmental burden?         |
| Political     | Industrial policy, incentives, R&D funding, technology sovereignty                                                               | Will governments support, steer or restrict development?          |
| Legal         | AI regulation, data protection, liability, safety certification, intellectual property                                           | How strictly and how quickly will law govern deployment?          |
| Ethical       | Job displacement, algorithmic bias, transparency, accountability                                                                 | Will deployment be perceived as fair and trustworthy?             |
| Media         | Public narratives about automation and AI; case studies of success or failure                                                    | Will public perception accelerate or slow acceptance?             |

#### **4.2 Social Forces**

Social forces concern the people who will build, operate and maintain the industrial metaverse. The most important social force is the composition and capability of the workforce. The aging skilled workforce holds the equipment knowledge that digital twins must encode, but many experienced professionals are wary of technologies that seem to devalue their expertise. The younger workforce is comfortable with digital interfaces but has not built that equipment knowledge (Sony and Naik, 2020). Adoption will only succeed if the metaverse is accessible to both groups and helps experienced professionals acquire new skills while helping newcomers acquire operational knowledge. User-centric design and change management are therefore not optional extras but determinants of the rate of adoption (Venkatesh et al., 2003; Akhigbe et al., 2024). Social acceptance by employees and other stakeholders is shaped by perceptions of job security, which ties social forces closely to ethical ones.

### **4.3 Technological Forces**

Technological advancement is the most critical driver. The capabilities and limitations of artificial intelligence, machine learning, robotics, digital twins and augmented reality determine the range of applications, the performance gains and the feasibility of use in complex industrial environments (Tao et al., 2019). Interoperability between systems from different vendors remains a major technical constraint, as proprietary data formats and siloed systems hinder the integration on which the metaverse depends (Xu et al., 2021). Cybersecurity is a second major technological force. Because the metaverse involves significant digital integration and data sharing across platforms and devices, its attack surface is large, and the ability to protect data and ensure system integrity will strongly influence adoption and trust. Edge computing, which processes data close to its source, will shape the architecture of real-time industrial applications (Shi et al., 2016). Interpretable machine learning for early failure prediction (Komi and Adamolekun, 2021) and edge intelligence for resilient control (Komi and Ganiu, 2023) illustrate the technical direction of the field, while AI and predictive analytics are being integrated into supply chain management (Rukh et al., 2024).

### **4.4 Economic Forces**

Economic forces center on the cost of implementation and the expected return. Organizations will justify capital expenditure based on expected efficiency gains, reduced downtime, improved maintenance capability and faster skill development. Large firms can spread platform costs across many sites, while small and medium-sized enterprises face prohibitive costs that may exclude them from the benefits (Müller et al., 2018). Market demand and competitive pressure push in the opposite direction: firms that see competitors gaining advantage from digital operations will feel compelled to invest. The economic force therefore combines high impact with moderate uncertainty, because the direction of costs, which are falling for computing and sensing but rising for integration and skilled labor, is reasonably predictable even if the distribution of benefits is not. Agile supply chain digital transformation with embedded risk controls shows how investment can be staged to manage economic exposure (Mbonu et al., 2020). Digital supply chain governance (Okonkwo et al., 2024a) and predictive procurement planning to sustain operational uptime (Okonkwo et al., 2024b) show how economic value is

captured, and quantitative risk architectures for public-private partnerships show how investment risk can be shared between public and private actors (Ike et al., 2024).

#### **4.5 Environmental Forces**

Environmental forces include pressure to reduce waste, energy consumption and emissions in manufacturing and logistics. Digital twins and artificial intelligence can optimize processes to reduce resource use, support predictive maintenance that extends equipment life, and enable circular economy models through lifecycle modelling (Stock and Seliger, 2016; Geissdoerfer et al., 2017). Companies that prioritize sustainability may therefore be more inclined to adopt metaverse technologies. Against this, the energy and water demands of computing infrastructure, including the data centers that host simulation and artificial intelligence workloads, are growing and attracting scrutiny (Amayo et al., 2024a). The net environmental effect is therefore contested, which gives the environmental force moderate impact and moderate uncertainty in this analysis.

#### **4.6 Political, Legal and Ethical Forces**

Political forces include government industrial policy, incentives such as tax relief and research funding, and concerns about technology sovereignty. Supportive policies can accelerate development and adoption, while restrictive or protectionist policies can fragment markets (Kagermann et al., 2013). Legal forces include the regulation of artificial intelligence, data protection, product liability and safety certification. A robust legal framework governing the use of artificial intelligence, robotics and augmented reality in industrial settings is essential, and compliance with data privacy, safety and artificial intelligence ethics requirements will become mandatory (European Union, 2024; NIST, 2023). Real-time compliance pipelines that automate risk monitoring offer one way for organizations to keep pace (Uchechi et al., 2022). Blockchain-based supply chain management has been studied as a way to strengthen transparency where institutional trust is weak (Ekwunife et al., 2024), and end-to-end visibility frameworks improve compliance and traceability across complex operations (Nnabueze et al., 2021).

Ethical forces include job displacement, bias and fairness in algorithms, and the transparency and accountability of automated decisions. Organizations must balance the benefits of adoption against potential social costs, ensuring fair workforce practices and retraining. Ensuring that

artificial intelligence systems are fair and unbiased in high-stakes industrial decisions is critical for maintaining trust (Mehrabi et al., 2021; Jobin et al., 2019). Political, legal and ethical forces are closely linked: ethical concerns drive public pressure, which drives political action, which produces legal requirements. Bias against increased adoption of artificial intelligence, together with concerns about data privacy, is likely to prompt governments to regulate these technologies to ensure safe and reliable adoption.

#### **4.7 Media Forces**

Media forces concern the public narratives that surround automation and artificial intelligence. High-profile accounts of job losses, accidents involving autonomous systems or data breaches can harden resistance among workers and the public and prompt regulatory responses, while credible case studies of safer, more satisfying work can build acceptance. Diffusion research shows that observability of results influences adoption rates (Rogers, 2003), and media coverage is one of the main channels through which results become observable beyond the organizations that achieve them. The media force has moderate impact and moderate uncertainty, but it amplifies other forces, particularly social, ethical and political ones. Organizations can influence it through transparent communication about the purposes and effects of their programs.

#### **4.8 Impact and Uncertainty Scoring**

Each force was scored for impact and uncertainty as described in Section 3. The combined priority score for force  $f$  is defined in Equation (1) as the sum of its impact score  $I_f$  and uncertainty score  $U_f$ .

$$S_f = I_f + U_f \quad (1)$$

Because a force with both high impact and high uncertainty matters more for scenario construction than one that is high on only one dimension, a normalized criticality index is also computed in Equation (2), which rewards forces that score highly on both.

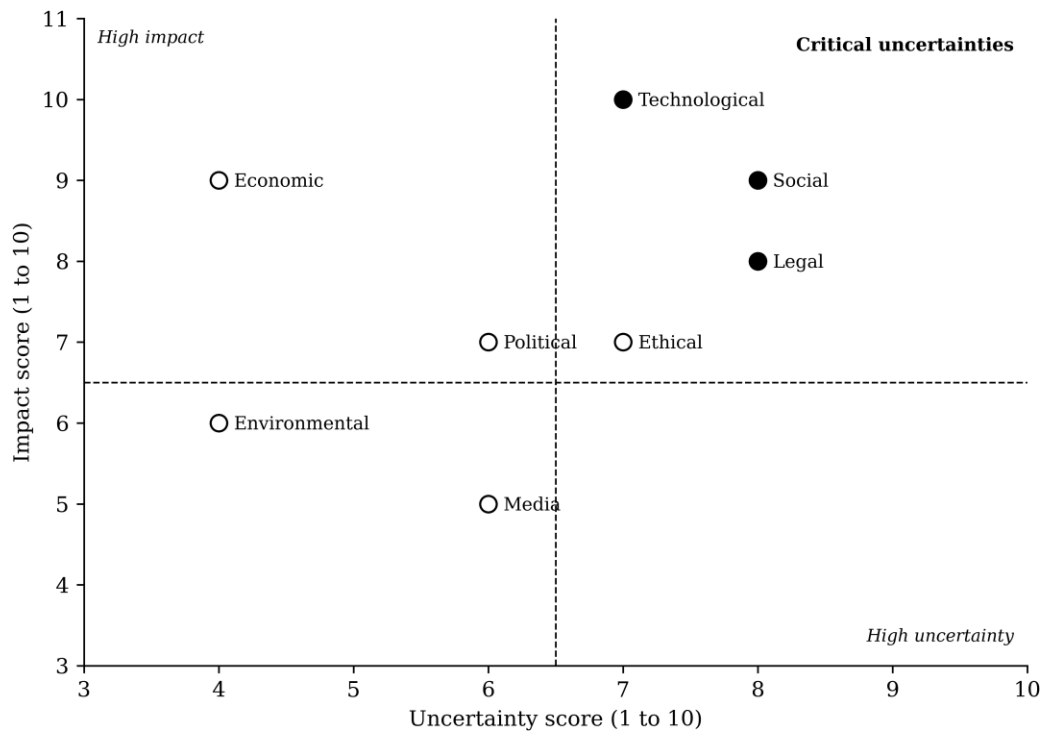
$$C_f = \frac{I_f \cdot U_f}{100} \quad (2)$$

Table 4 reports the scores. Technology, social and legal forces have the highest combined scores, followed by economic and ethical forces.

**Table 4.** Impact and uncertainty scores for the eight STEEPLEM forces

| Force         | Impact I | Uncertainty U | Score S | Criticality C | Rank by C |
|---------------|----------|---------------|---------|---------------|-----------|
| Social        | 9        | 8             | 17      | 0.72          | 1         |
| Technological | 10       | 7             | 17      | 0.70          | 2         |
| Legal         | 8        | 8             | 16      | 0.64          | 3         |
| Ethical       | 7        | 7             | 14      | 0.49          | 4         |
| Political     | 7        | 6             | 13      | 0.42          | 5         |
| Economic      | 9        | 4             | 13      | 0.36          | 6         |
| Media         | 5        | 6             | 11      | 0.30          | 7         |
| Environmental | 6        | 4             | 10      | 0.24          | 8         |

Figure 1 plots the forces on an impact-uncertainty grid. Social, technological and legal forces fall clearly in the upper right quadrant of critical uncertainties, with ethical forces at its edge. Economic forces have high impact but lower uncertainty, which marks them as important trends to plan for rather than uncertainties around which to build scenarios. This distinction between predetermined elements and critical uncertainties is the foundation of the scenario method (Schoemaker, 1995).



**Figure 1.** Impact-uncertainty grid for the eight STEEPLE forces; filled markers identify forces with combined scores of 16 or more.

#### 4.9 Monte Carlo Robustness of Force Scores

Because the impact and uncertainty scores in Table 4 rest on structured expert judgment, a Monte Carlo analysis with 10,000 draws was used to test whether the selection of critical uncertainties depends on the exact scores. In each draw, every impact and uncertainty score was shifted by minus one, zero or plus one, the criticality index was recomputed and the three highest-ranked forces were recorded. This form of perturbation analysis is a practical substitute for a full Delphi panel when testing the stability of expert-derived rankings (Amer et al., 2013). Table 5 reports the results.

**Table 5.** Probability that each force ranks among the three most critical across 10,000 perturbed draws

| Force         | Base criticality C | Probability in top three (%) |
|---------------|--------------------|------------------------------|
| Social        | 0.72               | 99.0                         |
| Technological | 0.70               | 93.9                         |
| Legal         | 0.64               | 91.8                         |
| Ethical       | 0.49               | 12.9                         |
| Political     | 0.42               | 1.6                          |

| Force         | Base criticality C | Probability in top three (%) |
|---------------|--------------------|------------------------------|
| Economic      | 0.36               | 0.7                          |
| Media         | 0.30               | 0.0                          |
| Environmental | 0.24               | 0.0                          |

Table 5 shows that social, technological and legal forces were among the three most critical in more than 90 percent of draws each, and that exactly these three formed the top three in 84.8 percent of draws. That statistic concerns the stability of the top three forces, not the choice of axes. Axis selection was therefore tested separately. Because social and technological forces both drive adoption, and legal and ethical forces both drive regulation, correlated forces were grouped into an adoption cluster and a regulation cluster, each taking the criticality of its most critical member, and the test asked whether these two clusters ranked first and second among the six resulting clusters. They did in 98.5 percent of draws. Individual forces alone would not support the same choice, since the two highest-ranked single forces were both adoption forces in about half of the draws, which is why intuitive logics practice builds axes from clusters of related drivers rather than from single forces (Schoemaker, 1995). The ethical force entered the top three in 12.9 percent of draws, which is consistent with its close link to the legal force; where it displaces the legal force, the regulation axis is still driven by ethical and legal pressure combined. The economic force almost never entered the top three despite its high impact, which supports its treatment as a predetermined trend rather than a critical uncertainty. The scenario axes are therefore robust to plausible disagreement about individual scores (Schoemaker, 1995).

#### **4.10 Alternative Scenario Axes**

Because the axes were derived from judgment-based scores, alternative axis pairs were also examined. Crossing the social and legal forces directly, rather than combining social and technological forces into an adoption axis, yields scenarios that differ mainly in workforce readiness under strong or weak regulation; these largely reproduce Scenarios A and C and lose the distinction between technical immaturity and organizational resistance. Crossing technological and economic forces yields scenarios driven by cost and capability, but the economic force has low uncertainty and therefore produces scenarios that differ little in strategic implications, which is why intuitive logics practice selects uncertain rather than merely

important drivers (Schoemaker, 1995). Interactions between drivers are also important: regulation can either suppress adoption, as in Compliance Drag, or enable it by building trust, as in Governed Convergence, and the direction depends on whether standards and certification arrive with the rules (Kagermann et al., 2013). The adoption and regulation axes were retained because they produce the most strategically distinct set of futures.

The adoption and regulation axes are sufficiently distinct because they are driven by different actors and evolve on different timescales: adoption depends mainly on firms, workers and technology suppliers and can change within a few years, whereas regulatory intensity depends on legislators and standards bodies and changes through slower legislative cycles. The two are correlated but not determined by each other, as the coexistence of strong regulation with both rapid and slow adoption in other technology domains shows (Marchant et al., 2011).

## **5. Scenario Construction**

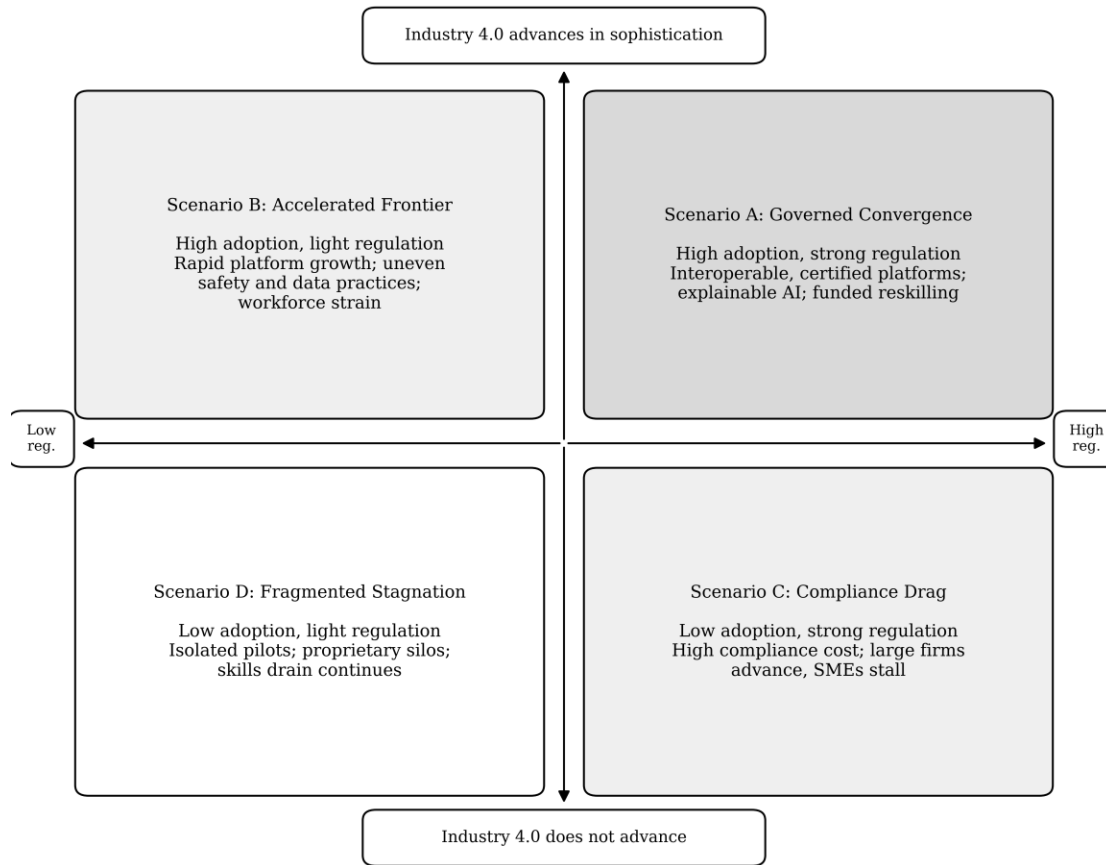
### **5.1 Selection of Scenario Axes**

Scenario axes should be the two critical uncertainties that are most important and most independent of each other (Schoemaker, 1995). The social and technological forces both bear on how far and how fast industrial metaverse technologies are adopted in practice: technology determines what is possible, and social factors determine what is taken up. They are therefore combined into a single vertical axis representing the degree of technology adoption, ranging from a future in which Industry 4.0 advances in sophistication through the infusion of emerging technology to one in which it does not. The legal force, together with its political and ethical drivers, forms the horizontal axis, representing the intensity of government regulation of artificial intelligence and related technologies in the metaverse, ranging from low to high. The two axes are conceptually independent: strong regulation can coexist with either high or low adoption, depending on whether regulation builds trust or imposes prohibitive burdens.

### **5.2 The Four Scenarios**

Crossing the two axes produces four scenarios, shown in Figure 2 and characterized in Table 6. Each scenario is internally consistent and plausible, and none is presented as a prediction. Their purpose is to stretch strategic thinking and to test the robustness of strategies (Wack, 1985; Ramírez and Wilkinson, 2016). Each scenario is described by the same set of dimensions,

including the state of technology, the regulatory environment, the role of the workforce and the position of smaller firms, so that differences between scenarios can be compared directly rather than inferred from narrative style (Wack, 1985). The scenarios are used in the following sections to test the robustness of strategic moves and to identify the signposts that would indicate which of them is emerging (Schoemaker, 1995).



**Figure 2.** Scenario matrix for the industrial metaverse, constructed on the axes of technology adoption and intensity of government regulation.

**Table 6.** Characteristics of the four industrial metaverse scenarios

| Dimension               | A: Governed Convergence                               | B: Accelerated Frontier                         | C: Compliance Drag                            | D: Fragmented Stagnation            |
|-------------------------|-------------------------------------------------------|-------------------------------------------------|-----------------------------------------------|-------------------------------------|
| Adoption and regulation | High adoption, strong regulation                      | High adoption, light regulation                 | Low adoption, strong regulation               | Low adoption, light regulation      |
| Platform landscape      | Interoperable, certified platforms built on standards | Rapid growth of competing proprietary platforms | Few platforms, concentrated among large firms | Isolated pilots and point solutions |

| Dimension    | A: Governed Convergence                                      | B: Accelerated Frontier                          | C: Compliance Drag                              | D: Fragmented Stagnation                        |
|--------------|--------------------------------------------------------------|--------------------------------------------------|-------------------------------------------------|-------------------------------------------------|
| Workforce    | Publicly supported reskilling; immersive training widespread | High demand for skills; strain and turnover      | Training tied to compliance; limited innovation | Skills drain continues as experts retire        |
| AI practices | Explainable, audited AI; clear accountability                | Fast deployment; uneven safety and bias controls | Conservative use; heavy documentation           | Ad hoc use without governance                   |
| SME position | Supported through shared platforms and subsidies             | Excluded unless they can buy in                  | Largely excluded by compliance cost             | Unaffected but falling behind                   |
| Main risk    | Slower innovation in some areas                              | Incidents that trigger backlash                  | Competitiveness loss to other regions           | Reliability decline as legacy knowledge is lost |

### 5.3 Scenario Narratives

In Governed Convergence, governments and industry co-develop standards and regulations that build trust in industrial artificial intelligence and digital twins. Certification of safety-relevant artificial intelligence and interoperability standards reduce integration costs, and public funding supports reskilling through immersive training. Adoption is broad and steady. The metaverse becomes a shared infrastructure for maintenance, training and collaboration across firms and supply chains. Regulation slows some experimentation, but the overall trajectory is positive. Responsible artificial intelligence governance structures of the kind already emerging in regulated industries are the norm (Ominyi and Anichukwueze, 2024).

In Accelerated Frontier, adoption races ahead of regulation. Large technology providers and manufacturers deploy integrated platforms quickly, and early movers capture significant productivity gains. However, safety, data and bias practices are uneven, the workforce struggles to keep pace, and the risk of high-profile incidents is elevated. A serious accident or data breach could trigger a sharp regulatory response, moving the system abruptly toward the right side of the matrix.

In Compliance Drag, regulation tightens before technologies mature, and the cost of compliance slows adoption. Large firms with dedicated compliance functions continue to invest, but small and medium-sized enterprises are largely excluded. Innovation shifts to regions with lighter regulation, raising concerns about competitiveness and technology sovereignty. Training focuses on compliance rather than capability. In Fragmented Stagnation, neither strong regulation nor

broad adoption materializes. Organizations run isolated pilots that do not scale, proprietary systems remain siloed, and the skills drain continues as experienced professionals retire without their knowledge being captured. Reliability gradually declines in organizations that fail to modernize.

## 6. Emergent Patterns and Future Logics

### 6.1 Patterns Arising from Force Interactions

The interplay of STEEPLM forces gives rise to several patterns that hold across scenarios, although their strength varies. Table 7 summarizes six patterns, each arising from the interaction of two or more forces, together with the organizational logic that each pattern implies.

**Table 7.** Emergent patterns arising from STEEPLM force interactions and the organizational logic they imply

| Interacting forces              | Emergent pattern                                                                                | Implied organizational logic                                           |
|---------------------------------|-------------------------------------------------------------------------------------------------|------------------------------------------------------------------------|
| Technological and economic      | Innovation-driven growth: technology gains create economic returns that fund further investment | Prioritize innovations with demonstrable cost-benefit and ROI          |
| Social and technological        | Workforce evolution and widening skill gap if training lags technology                          | User-centric design; invest in training alongside technology           |
| Legal and ethical               | Regulatory lag and compliance uncertainty                                                       | Proactive compliance and ethical AI by design                          |
| Economic and social             | Unequal access between large firms and SMEs                                                     | Public-private partnerships and shared platforms                       |
| Technological and ethical       | Algorithmic bias and accountability dilemmas                                                    | Algorithmic transparency, fairness review and AI governance committees |
| Environmental and technological | Green technology adoption and eco-innovation                                                    | Treat sustainability as a competitive advantage                        |

The first pattern in Table 7 is a technological and economic synergy. Advances in artificial intelligence, robotics, machine learning, digital twins and augmented reality drive economic growth by enabling more efficient, reliable and cost-effective industrial processes, and the resulting returns fund further investment, creating a feedback loop (Brynjolfsson and McAfee, 2014). The organizational logic is cost-benefit analysis: technologies that demonstrate clear economic benefits, such as reduced maintenance cost, improved uptime or higher productivity, are adopted first. Performance intelligence models that measure outcomes in large-scale operations help organizations decide which innovations to scale (Adelanwa et al., 2024).

The second pattern arises at the social-technical interface. Advanced technologies shift the skills required, creating both an opportunity and a challenge, and the skills gap widens if training does not keep pace (Sony and Naik, 2020). The logic is user-centric design: technologies that fit existing workflows, have intuitive interfaces and come with support are adopted more readily. The third pattern is regulatory lag, in which law struggles to keep pace with technology, creating compliance uncertainty (Marchant et al., 2011). The logic is proactive compliance: organizations anticipate regulation and build ethical considerations such as transparency, fairness and accountability into their artificial intelligence systems from the start.

The fourth pattern concerns economic inequality in access to technology. High costs mean that only well-funded organizations can implement metaverse solutions, potentially widening the gap between large corporations and smaller firms. Public-private partnerships, subsidies and shared platforms lower barriers to entry (Müller et al., 2018; Ike et al., 2021). The fifth pattern concerns algorithmic bias and accountability, which can lead to unfair treatment of employee groups or poor maintenance decisions; the logic is governance through transparency, fairness review and ethics committees (Mehrabi et al., 2021). The sixth pattern is green technology adoption, in which digital twins and artificial intelligence are used to optimize resource efficiency, and sustainability becomes a source of competitive advantage (Kiel et al., 2017; Okojie et al., 2023).

## **6.2 Nine Future Logics**

From the scenarios and patterns, nine future logics emerge that describe the likely direction of strategy in the industrial metaverse. The logics are interdependent rather than separate, since convergence enables data-driven decisions and human-AI collaboration, while regulatory co-evolution conditions all of them. They are summarized in Table 8 with the forces that drive them.

**Table 8.** Nine future logics for the industrial metaverse and their principal driving forces

| <b>Future logic</b>            | <b>Core idea</b>                                                                   | <b>Principal driving forces</b> |
|--------------------------------|------------------------------------------------------------------------------------|---------------------------------|
| Convergence                    | Unified platforms integrating AI, digital twins and AR; interoperability standards | Technological, economic         |
| Adaptive and resilient systems | Modular, flexible adoption; resilient supply chains modelled with twins            | Economic, political             |
| Data-driven decision-making    | Predictive and prescriptive maintenance; continuous learning models                | Technological, economic         |

| Future logic                          | Core idea                                                             | Principal driving forces |
|---------------------------------------|-----------------------------------------------------------------------|--------------------------|
| Human-AI collaboration                | Augmented intelligence with humans deciding; AR and VR for upskilling | Social, ethical          |
| Sustainability and circular economy   | Resource optimization; lifecycle modelling for reuse and recycling    | Environmental, economic  |
| Ethical and transparent AI            | Explainable models; ethical governance frameworks                     | Ethical, legal, media    |
| Decentralized and distributed systems | Edge computing; decentralized AI; blockchain for traceability         | Technological, legal     |
| Regulatory co-evolution               | Dynamic regulation; proactive compliance                              | Legal, political         |
| Geopolitical and strategic            | Technology sovereignty balanced with international standards          | Political, economic      |

The convergence logic holds that different technologies will be integrated into unified platforms that create a seamless flow of data and insight, supported by interoperability standards that reduce the barriers created by proprietary systems (Xu et al., 2021). The adaptive and resilient systems logic favors flexible, modular adoption strategies and supply chains modelled with digital twins to predict and absorb disruptions (Ivanov and Dolgui, 2021). The data-driven decision logic centers on predictive and prescriptive maintenance, in which data from twins and sensors are analyzed in real time to forecast failures and recommend actions, and on continuous learning systems that improve as data accumulate (Tao et al., 2019).

The human-AI collaboration logic replaces the idea of artificial intelligence substituting for people with augmented intelligence, in which artificial intelligence offers insight and recommendations while humans make final decisions, and in which immersive technologies train and upskill workers (Nahavandi, 2019). The sustainability logic uses digital twins to optimize resource use and to model circular processes (Geissdoerfer et al., 2017). The ethical and transparent artificial intelligence logic calls for explainable models and governance frameworks that minimize bias (Floridi et al., 2018). The decentralized systems logic relies on edge computing for low-latency decisions and on blockchain for secure, transparent data sharing in supply chains (Shi et al., 2016; Saberi et al., 2019). The regulatory co-evolution logic anticipates more dynamic regulation that adapts to technological change, rewarding organizations that comply proactively (NIST, 2023). The geopolitical logic balances technology sovereignty, which

favors domestic capability, against international collaboration on standards that facilitates trade (Kagermann et al., 2013).

## **7. Triage Framework and Strategic Direction**

### **7.1 Triage of Forces**

Organizations cannot respond to every force simultaneously. Triage in this context means prioritizing forces by their potential impact, their urgency and their relevance to strategic goals. The criticality index from Equation (2) captures impact and uncertainty; urgency adds the time dimension. The triage priority for force  $f$  is defined in Equation (3), where  $C_f$  is the criticality index and  $v_f$  is an urgency factor between 0 and 1 reflecting how soon the force will require action.

$$P_f = C_f \cdot v_f \quad (3)$$

Urgency depends on context. For an organization facing imminent regulation in a major market, the legal force has high urgency; for one with a large cohort of technicians nearing retirement, the social force is most urgent; for one under budget pressure, economic considerations are most urgent because of investment cycles. The triage priority therefore varies across organizations even when criticality is shared, which is why the framework asks each organization to set its own urgency factors. Scenario-based financial modelling can support this step by testing how investment returns vary across scenarios (Filani et al., 2023).

### **7.2 The Eight-Step Triage Process**

The triage framework comprises eight steps that together form a continuous management cycle. First, assessment and prioritization: organizations assess the impact, urgency and risks of each force in their specific context, giving priority to high-impact areas such as artificial intelligence capability and cybersecurity. Second, strategic alignment and planning: they build a technology roadmap prioritizing investments by readiness, integration complexity and return, develop compliance strategies, and plan workforce development. Third, resource allocation: budgets and talent are directed to high-priority areas, potentially through centers of excellence for artificial intelligence, cybersecurity and compliance. Fourth, scenario planning and contingency development: plans are tested against the four scenarios, and contingency plans are prepared, for

example additional change management if workforce resistance becomes significant (Schoemaker, 1995). Effective project governance in multinational infrastructure programs (Amayo et al., 2024b) and strategic project management for emerging-market energy deployments (Amayo et al., 2024c) offer practical templates for the governance step.

Fifth, monitoring and feedback: performance indicators track adoption rates, return on investment, training progress and compliance status, and feedback loops such as employee surveys detect emerging social or ethical concerns. Sixth, cross-functional collaboration and governance: teams drawn from technology, operations, legal, compliance and human resources address multifaceted challenges, overseen by steering committees with clear decision rights. Seventh, stakeholder engagement and communication: organizations engage internal and external stakeholders and communicate benefits, risks and progress transparently, which also shapes media narratives. Eighth, continuous innovation and adaptation: innovation sprints, partnerships with startups and academic institutions, and agile management methods keep the organization responsive (Rohrbeck and Kum, 2018). Data sensitivity classification and regulatory traceability mechanisms underpin several of these steps by ensuring that data flowing through the metaverse is governed appropriately (Aliliele et al., 2024).

### **7.3 No-Regret Strategic Moves**

Scenario-based strategy distinguishes no-regret moves, which create value in every scenario, from contingent moves suited to particular futures (Ramírez and Wilkinson, 2016). Table 9 tests six candidate moves against the four scenarios.

**Table 9.** Robustness of candidate strategic moves across the four scenarios (H = high value, M = moderate value, L = low value)

| Strategic move                                       | A: Governed Convergence | B: Accelerated Frontier | C: Compliance Drag | D: Fragmented Stagnation |
|------------------------------------------------------|-------------------------|-------------------------|--------------------|--------------------------|
| Interoperable, standards-based platform architecture | H                       | M                       | H                  | M                        |
| Explainable AI and model governance                  | H                       | H                       | H                  | M                        |
| Immersive, twin-based workforce reskilling           | H                       | H                       | M                  | H                        |
| Tacit knowledge capture from experienced technicians | H                       | H                       | H                  | H                        |

| Strategic move                           | A: Governed Convergence | B: Accelerated Frontier | C: Compliance Drag | D: Fragmented Stagnation |
|------------------------------------------|-------------------------|-------------------------|--------------------|--------------------------|
| Proactive compliance and data governance | H                       | M                       | H                  | L                        |
| Large proprietary platform lock-in       | L                       | H                       | L                  | L                        |

Four moves score highly in all or nearly all scenarios. Tacit knowledge capture from experienced technicians is valuable in every future, because the knowledge is lost permanently if it is not captured and is useful whether or not advanced platforms are adopted. Immersive, twin-based workforce reskilling and explainable artificial intelligence with model governance score highly in three scenarios and moderately in the fourth. Interoperable architecture scores well across scenarios and protects against lock-in. Large proprietary platform lock-in, by contrast, pays off only in the Accelerated Frontier scenario and carries significant downside elsewhere, which marks it as a contingent rather than no-regret move. Organizations that combine the no-regret moves with a watching brief on scenario signposts can adapt as the future unfolds. Digital transformation that integrates automation with explicit risk reduction offers a practical template for sequencing these moves (Sakyi et al., 2024b).

#### **7.4 Formal Robustness Test Using Minimax Regret**

The qualitative robustness ratings in Table 9 can be tested formally with decision criteria designed for deep uncertainty, where probabilities cannot be assigned to scenarios with confidence (Lempert et al., 2003; Walker et al., 2013). The minimax regret criterion, introduced by Savage (1951), selects the option whose worst-case regret is smallest. Coding high, moderate and low value as 3, 2 and 1, the regret of move  $m$  in scenario  $s$  is the shortfall against the best move in that scenario, as given in Equation (4).

$$r_{ms} = \max_{m'} v_{m's} - v_{ms} \quad (4)$$

The maximum regret of each move across scenarios is then given by Equation (5).

$$MR_m = \max_s r_{ms} \quad (5)$$

Table 10 reports the regrets and their maximum for each candidate move, together with the mean value across scenarios.

**Table 10.** Regret analysis of candidate strategic moves across the four scenarios

| Strategic move                              | Regret A | Regret B | Regret C | Regret D | Maximum regret | Mean value |
|---------------------------------------------|----------|----------|----------|----------|----------------|------------|
| Tacit knowledge capture                     | 0        | 0        | 0        | 0        | 0              | 3.00       |
| Explainable AI and model governance         | 0        | 0        | 0        | 1        | 1              | 2.75       |
| Immersive, twin-based reskilling            | 0        | 0        | 1        | 0        | 1              | 2.75       |
| Interoperable, standards-based architecture | 0        | 1        | 0        | 1        | 1              | 2.50       |
| Proactive compliance and data governance    | 0        | 1        | 0        | 2        | 2              | 2.25       |
| Large proprietary platform lock-in          | 2        | 0        | 2        | 2        | 2              | 1.50       |

The analysis in Table 10 is consistent with the qualitative judgment, within the assigned payoff matrix. Tacit knowledge capture has zero regret in every scenario and is therefore dominant. Explainable AI, immersive reskilling and interoperable architecture each carry a maximum regret of one and form a robust second tier. Proprietary lock-in carries the joint-highest maximum regret and the lowest mean value, and it is the only move whose value depends on a single scenario materializing. Because minimax regret does not require scenario probabilities, it is well suited to deep uncertainty, but it inherits the assumption that high, moderate and low values are equally spaced. Repeating the analysis with convex scales of 1, 2 and 4 and of 1, 3 and 9, and with a concave scale of 1, 2.5 and 3, left the ordering unchanged: tacit knowledge capture retained zero regret, the second tier remained explainable AI, immersive reskilling and interoperable architecture, and lock-in and proactive compliance remained last. The ranking is therefore insensitive to the spacing of the scale, although it would change if the payoff judgments themselves changed, and it does not account for implementation cost, dependencies between moves or organizational constraints, which a fuller analysis should add (Walker et al., 2013).

Two qualifications apply to the regret analysis. First, it was repeated under 10,000 randomly drawn monotone scales in which the moderate value lay anywhere between 1.01 and 10 and the high value anywhere between the moderate value and ten times it; tacit knowledge capture remained the unique zero-regret move and proprietary lock-in remained among the highest-regret moves in every draw. Second, and more fundamentally, the zero regret of tacit knowledge capture follows directly from its being rated high in every scenario in Table 9; the analysis therefore shows the consequence of that payoff judgment rather than establishing the move's

superiority independently. Independent stakeholder ratings of the payoffs, together with implementation costs and dependencies between moves, would be needed before the ranking could be treated as a recommendation beyond the assigned payoff matrix (Walker et al., 2013).

### **7.5 Signposts for Scenario Monitoring**

Scenarios are most useful when organizations monitor signposts that indicate which future is emerging (Schoemaker, 1995). For the adoption axis, signposts include the rate of interoperability standard adoption, the cost trajectory of sensors and extended reality hardware, the share of maintenance work orders supported by digital twins, and the uptake of immersive training. For the regulation axis, signposts include the progress of artificial intelligence legislation and implementing standards, enforcement actions, certification schemes for safety-relevant artificial intelligence, and data localization requirements. European Union (2024) showed that organizational readiness for artificial intelligence regulation varies widely, suggesting that internal readiness assessments are themselves a useful signpost. Lean and agile methods for high-velocity operations offer approaches for adjusting quickly once signposts shift (Nwangwu et al., 2024).

## **8. Discussion**

### **8.1 Theoretical Implications**

This study extends strategic foresight research into the specific domain of the industrial metaverse for maintenance and advanced manufacturing. Its main theoretical contribution is to show that the decisive uncertainties are not purely technological. Technology, social acceptance and regulation share the highest criticality scores, and the scenario axes combine them. This finding supports socio-technical perspectives on Industry 4.0 that argue outcomes depend on the joint evolution of technology and institutions (Sony and Naik, 2020), and it qualifies technology-centric accounts that treat adoption as a function of capability alone. The six emergent patterns provide a vocabulary for analysing force interactions that could be tested empirically, for example by examining whether firms that invest in training alongside technology experience faster adoption.

The study also links foresight to governance research. The regulatory lag and ethical artificial intelligence patterns connect the pacing problem described by Marchant et al. (2011) to the

organizational practice of proactive compliance. The robustness analysis suggests that explainable artificial intelligence and model governance are not merely compliance costs but no-regret moves, which supports the view that responsible artificial intelligence and competitive performance can be aligned (Floridi et al., 2018; Ominyi and Anichukwueze, 2023).

### **8.2 Managerial Implications**

For industrial leaders, the analysis has three practical implications. First, investment in the industrial metaverse should begin with no-regret moves that pay off whatever the future holds: capture tacit knowledge, build interoperable architecture, adopt explainable artificial intelligence with governance, and invest in immersive reskilling. These moves reduce downside risk while positioning the organization to benefit if adoption accelerates. Second, leaders should treat workforce and regulation as strategic variables rather than constraints to be managed after technology decisions are made. The highest criticality scores belong to social and legal forces, and strategies that ignore them are likely to fail regardless of technical merit.

Third, organizations should institutionalize foresight through regular scanning, scenario review and signpost monitoring. Corporate foresight is associated with superior performance when it is embedded in strategy and resource allocation (Rohrbeck and Kum, 2018). For maintenance and reliability functions, this means participating in strategic planning rather than receiving technology decisions after the fact, since maintenance leaders hold critical insight into workforce capability and equipment realities. Smaller firms should seek partnerships and shared platforms to overcome cost barriers, and policymakers should consider subsidies and collaborative initiatives to avoid a two-tier industrial landscape (Müller et al., 2018).

### **8.3 Theoretical Propositions and Research Agenda**

The scenarios and triage framework imply propositions that can be tested as the industrial metaverse develops. Table 11 states five propositions with constructs and research designs. They draw on corporate foresight research (Rohrbeck and Kum, 2018), on the pacing problem in technology regulation (Marchant et al., 2011) and on diffusion theory (Rogers, 2003).

**Table 11.** Testable propositions derived from the foresight analysis

| Proposition                            | Constructs          | Suggested test design               |
|----------------------------------------|---------------------|-------------------------------------|
| P1. Organizations that adopt no-regret | No-regret adoption; | Longitudinal panel of manufacturers |

| Proposition                                                                                                                                          | Constructs                                 | Suggested test design                              |
|------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------|----------------------------------------------------|
| moves early show lower variance in returns on digital investment across the scenario that materializes                                               | variance of returns                        | with investment and performance data               |
| P2. Under strong regulation, organizations with proactive compliance capabilities adopt industrial metaverse technologies faster than those without  | Compliance maturity; adoption speed        | Comparative case studies across regulatory regimes |
| P3. Investment in tacit knowledge capture is associated with smaller reliability declines during workforce retirement waves                          | Capture investment; reliability change     | Interrupted time-series around retirement cohorts  |
| P4. The adoption rate of interoperability standards is a leading indicator of movement toward the Governed Convergence scenario                      | Standards adoption; platform integration   | Signpost tracking over several years               |
| P5. Small and medium-sized enterprises participate more in industrial metaverse adoption where shared platforms or public-private partnerships exist | Shared platform availability; SME adoption | Regional comparison of adoption surveys            |

Testing these propositions would convert the scenario analysis from a planning tool into a source of cumulative evidence about how emerging industrial technologies are adopted under uncertainty, addressing calls for foresight research to examine its effects on organizational outcomes (Rohrbeck and Kum, 2018). Following the guidance that conceptual articles should state propositions precisely enough to be refuted (Jaakkola, 2020), each proposition names the constructs involved and the evidence that would count against it: a proposition is not supported if the predicted relationship is absent, or reversed, when its constructs are measured as specified. Because several constructs are newly defined in this paper, establishing valid measures of them is a precondition for testing the propositions themselves.

#### **8.4 Limitations and Future Research**

The analysis has limitations. Force scores were assigned through expert judgment informed by literature rather than through a formal Delphi panel or survey, and different experts might assign different scores. Future research could validate the scores using a Delphi study with maintenance, manufacturing, technology and policy experts, an approach well established in foresight research (Amer et al., 2013). The scenarios use intuitive logics and are qualitative; quantitative modelling of adoption trajectories under different regulatory regimes could

complement them. The force scores and payoffs reflect the judgment of a single author; independent assessments by a panel of maintenance leaders, technology suppliers, regulators and workforce representatives would test whether the critical uncertainties and payoffs generalize (Amer et al., 2013).

The analysis focuses on maintenance and advanced manufacturing in industrialized economies, and the relative weight of forces may differ in emerging economies where infrastructure, skills and regulatory capacity differ. Comparative studies across regions would be valuable. Finally, the industrial metaverse is evolving rapidly, and the scenarios should be revisited as signposts develop. Longitudinal research tracking which scenario emerges, and how organizations that adopted no-regret moves fare, would provide a test of the framework's practical value (Rohrbeck and Kum, 2018).

## **9. Conclusion**

The fusion of artificial intelligence, robotics, machine learning, digital twins and augmented reality into an industrial metaverse holds significant potential for maintenance, advanced manufacturing and skill development. Its development, however, depends on the interaction of social, technological, economic, environmental, political, legal, ethical and media forces, and the future cannot be predicted from technology trends alone.

This paper has applied a STEEPLM foresight analysis to identify technology adoption and the intensity of regulation as the critical uncertainties, constructed four scenarios around them, traced six emergent patterns and nine future logics, and proposed a triage framework with no-regret strategic moves. The central finding is that the people who must adopt the technologies and the rules that govern them matter as much as the technologies themselves.

Organizations that capture the knowledge of their experienced workforce, build interoperable and explainable systems, invest in immersive reskilling and engage proactively with regulation will be positioned to benefit across a wide range of futures. By treating the industrial metaverse as a strategic question to be navigated rather than a technology to be bought, industrial leaders can harness its potential while managing its risks to their workforce, their operations and the communities they serve.

## Declarations

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Data availability: All parameter values and results are reported in the article. The simulation code, input files, random seeds and distribution settings that reproduce every numerical table are available from the corresponding author on reasonable request.

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