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Bridging Model-Based Systems Engineering, Digital Twins, and Cyber-Physical Manufacturing Systems: A Foundational Framework for Operational Excellence

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Abstract. The accelerating complexity of modern manufacturing demands a unified approach to align system design, operational execution, and continuous improvement. Model-Based Systems Engineering (MBSE), Digital Twins (DTs), and Manufacturing Operations Management (MOM) each contribute critical but fragmented capabilities across this continuum, while Cyber-Physical Systems (CPS) enable real-time coupling between digital and physical layers. Despite their conceptual complementarity, the literature lacks an integrative framework that connects these domains into a continuous information and decision flow supporting Operational Excellence. This paper conducts a systematic bibliographic synthesis of 97 peer-reviewed studies and standards (INCOSE, ISO 23247, ISA-95) to develop the Dynamic Digital Thread Framework (DDTF)—a foundational architecture for digitally continuous, cyber-physical manufacturing ecosystems. The DDTF aligns MBSE's model-centric discipline with DT's analytical intelligence, MOM's executional control, and CPS's real-time adaptability. Through this integration, the framework operationalizes Lean and Six Sigma principles within a digital architecture capable of reducing conversion cost, synchronizing the 4Ms (Man, Machine, Material, Method), and eliminating non-value-added activities.
The study contributes a theoretically grounded yet industry-relevant foundation for future empirical research on digital continuity and cyber-physical integration. By reframing digital transformation as a systemic redefinition of knowledge flow and decision logic—rather than a technology deployment—the DDTF establishes a conceptual bridge between engineering intent and operational reality, enabling sustainable Operational Excellence in the era of Industry 5.0.

Keywords: Model-Based Systems Engineering; Digital Twin; Manufacturing Operations Management; Digital Thread, Dynamic Digital Thread Framework (DDTF).

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1. Introduction

1.1. Context and Motivation

Manufacturing industries are undergoing a profound transformation driven by the convergence of digitalization, automation, and intelligent systems. The emergence of Industry 4.0 and the forthcoming Industry 5.0 paradigms have placed increasing emphasis on data-driven integration between design, production, and operations (Kamble, Gunasekaran, & Gawankar, 2020; McKinsey & Company, 2024). Within this context, the synergy among Model-Based Systems Engineering (MBSE), Digital Twins (DTs), and Manufacturing Operations Management (MOM) represents a strategic pathway for achieving Operational Excellence—a state of continuous improvement, waste minimization, and system adaptability (Schroeder, 2020).

MBSE provides the architectural backbone for defining, designing, and validating complex systems across their life cycle. Unlike document-based engineering, MBSE employs digital models as the single source of truth, ensuring traceability from stakeholder requirements to system verification (INCOSE, 2023). This model-centric paradigm facilitates cross-disciplinary integration and enables early verification of design intent against functional and operational constraints (Vogelsang, Eder, Hackenberg, & Keuler, 2017).

In parallel, Digital Twins extend MBSE principles into the operational realm. DTs are dynamic, data-driven virtual counterparts of physical systems that enable continuous monitoring, simulation, and optimization (Lu, Liu, Wang., Huang & Xu, 2020). The synchronization between sensor data and simulation models allows for predictive maintenance, performance optimization, and scenario-based decision-making—capabilities essential to modern manufacturing intelligence (Kritzinger, Karner, & Traar, 2018; Uhlemann, Lehmann, & Steinhilper, 2017).

However, despite the shared vision of integration, MBSE and DT initiatives are frequently implemented in isolation. MBSE focuses on the design intent, while DTs address the operational state, leaving a gap between system design and execution. This separation hinders realization of a continuous digital thread that could connect design, production, and feedback. MOM and CPS can serve as the missing link, enabling bidirectional synchronization between virtual models and real-world operations (Lee, Davari, Singh, & Pandhare, 2020; Monostori, Kádár, Bauernhansl, Kondoh, & Ueda, 2016).

Therefore, this bibliographic research consolidates the theoretical and practical foundations of MBSE, DT, MOM, and CPS to propose the Dynamic Digital Thread Framework (DDTF) that unites them under a common goal: enabling Operational Excellence through digital continuity, real-time adaptability, and systemic learning.

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1.2. Industrial Need for Integration

Modern manufacturing systems face increasing pressure to deliver mass customization, shorter time-to-market, and sustainable production (Buer, Strandhagen, & Chan, 2021; Jasiulewicz-Kaczmarek & Gola, 2019). While traditional methodologies such as Lean Manufacturing and Six Sigma have enhanced localized efficiency, they lack systemic integration across design and operations. The challenge lies in connecting the "intent" of engineering with the "reality" of production, ensuring that design assumptions remain valid under dynamic shop-floor conditions (Sanders, Elangeswaran, & Wulfsberg, 2019).

MBSE provides the structural language to describe system interdependencies, while Digital Twins operationalize this knowledge by feeding models with live performance data. MOM systems mediate between the two, orchestrating production scheduling, quality control, and resource management (Lee & Seshia, 2015). This triad supports closed-loop optimization, where design models evolve based on real-time operational evidence (Stark, Fresemann, & Lindow, 2019).

Integration also addresses a key economic driver: conversion-cost optimization. Conversion costs—labor, machine utilization, and overhead—represent a major share of manufacturing expenses (Bokrantz, Skoogh, Berlin, & Stahre, 2020). By aligning MBSE-defined parameters (e.g., cycle times, tolerances) with DT-monitored performance, organizations can quantify deviations, trace inefficiencies, and enhance cost predictability (Dombrowski & Wagner, 2014).

Moreover, integrating MBSE and DT through MOM facilitates the identification and elimination of non-value-added (NVA) activities. MBSE models simulate ideal workflows, while DTs validate them against actual conditions, allowing organizations to refine process design and resource allocation (Kolberg & Zühlke, 2015; Negri, Fumagalli, & Macchi, 2017; Womack & Jones, 2003).1.3 Theoretical Foundations

The integration of MBSE, DT, MOM, and CPS creates a hierarchical yet interconnected ecosystem spanning the entire manufacturing life cycle (Lee, Yeo, Kim & Mun, 2022).

Model-Based Systems Engineering (MBSE) offers a formalized modeling framework that ensures traceability and coherence across the system life cycle (INCOSE, 2023). Through SysML and ontology-based structures, MBSE supports manufacturability-by-design by embedding process and resource constraints early in design (Ramos, Ferreira, & Barceló, 2012).

DTs represent the analytical counterpart of physical systems, characterized by continuous data synchronization and simulation capabilities. A DT evolves through physical, virtual, and connective layers, with maturity defined by its ability not only

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to mirror but also to influence physical performance (Grieves & Vickers, 2017; Fuller, Fan, Day, & Barlow, 2020; Qi & Tao, 2018).

MOM provides the executional intelligence of the enterprise, connecting planning and control through standardized architectures such as ISA-95 (Lasi, Fettke, Kemper, Feld, & Hoffmann, 2014). When linked with MBSE and DTs, MOM enables dynamic synchronization between design assumptions and operational performance (Grosvenor, Charnley, & Bhamra, 2020; Kang et al., 2016).

Finally, CPS enable real-time coupling between computational logic and physical execution, ensuring continuous synchronization of MBSE and DT through sensor feedback, distributed intelligence, and edge computation (Lee & Seshia, 2015; Monostori, 2014; Lu, Morris, & Frechette, 2016).

Together, these elements define the digital thread—a continuous flow of knowledge linking design, simulation, and execution within a single adaptive manufacturing framework (Wollschlaeger, Sauter, & Jasperneite, 2017).

1.4. Research Gap and Objectives

Although research in MBSE, DT, and MOM has matured individually, their synergistic integration remains underdeveloped. Existing literature often treats these domains in isolation, lacking a unified framework for continuous data and model exchange (Rosen, Von Wichert, Lo, & Bettenhausen, 2015; Madni & Sievers, 2018). Moreover, CPS-despite its critical role in connecting digital and physical layers-has not been fully explored as the enabler of semantic and real-time synchronization between MBSE and DTs (Monostori, 2014; Tao et al., 2019).

This research therefore seeks to fill that gap by developing a bibliographic synthesis that:

1. Integrates theoretical constructs across MBSE, DT, MOM, and CPS.
2. Defines the principles required to achieve digital continuity and Operational Excellence.
3. Proposes a conceptual DDTF as the foundation for future empirical research.

2. Method

2.1. Research Design

This research adopts a bibliographic and conceptual design, emphasizing synthesis rather than empirical validation. The primary objective is to consolidate fragmented bodies of knowledge related to Model-Based Systems Engineering (MBSE), DTs, MOM, and CPS and to propose a foundational conceptual framework for their integration within manufacturing systems. Conceptual designs are particularly appropriate for emerging interdisciplinary fields, as they enable the development of theoretical coherence before large-scale implementation or experimentation (Jaakkola, 2020; Snyder, 2019).

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The study is grounded in Systematic Literature Review (SLR) principles, following the structured methodology proposed by Tranfield, Denyer, and Smart (2003) and expanded by Kitchenham (2007). The SLR approach was selected to ensure methodological rigor, transparency, and reproducibility-key requirements for credible academic synthesis (Booth, Sutton, & Papaioannou, 2016). The SLR process distinguishes itself from narrative reviews by enforcing structured search, classification, and analysis steps to mitigate bias (Okoli, 2015). The research followed a three-phase process:

1. Planning Phase: Defining research objectives, scope, and key questions; selecting databases; and determining inclusion/exclusion criteria.
2. Execution Phase: Conducting database searches, screening results, and classifying relevant studies.
3. Synthesis Phase: Integrating findings into a conceptual framework guided by systems thinking and manufacturing principles such as the 4Ms (Man, Machine, Material, Method) and conversion cost optimization (Ohno, 1988; Womack & Jones, 2003).

Each phase was documented to ensure replicability and traceability, consistent with ISO 9001 documentation principles and INCOSE MBSE research guidelines (INCOSE, 2023; ISO, 2021).

This process enables the construction of an evidence-based conceptual model-grounded in verified sources, structured reasoning, and theoretical alignment-capable of guiding future empirical investigations in MBSE-DT-MOM-CPS integration (Madni & Sievers, 2018; Grieves & Vickers, 2017).

2.2. Research Paradigm and Epistemological Orientation

This study adopts a constructivist epistemology and a systems-thinking paradigm, both essential to understanding the complex socio-technical dynamics of digital manufacturing. Constructivism holds that knowledge is created through interaction between academic and industrial communities rather than existing independently of them (Guba & Lincoln, 1994; Creswell & Creswell, 2018). Systems thinking, meanwhile, provides a framework for analyzing relationships among interdependent subsystems-technical, organizational, and cyber-physical-that together constitute modern manufacturing ecosystems (Checkland, 1999 & Senge, 2006).

From this philosophical standpoint, the research assumes that no single domain-engineering, manufacturing, or IT-can independently achieve digital continuity. Instead, it views MBSE, DT, MOM, and CPS as mutually reinforcing pillars that collectively enable operational adaptability and learning (Hollnagel, 2014; Sterman, 2000).

- MBSE provides the top-down logic for system design and traceability (Friedenthal, Moore, & Steiner, 2015; Estefan, 2008).

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- DT delivers the analytical and simulation intelligence needed for system validation and performance optimization (Tao et al., 2020).
- MOM governs bottom-up executional intelligence, translating high-level intent into real-world operations (ISA, 2010).
- CPS acts as the connective tissue enabling bidirectional feedback between digital models and physical assets (Lee & Seshia, 2015; Monostori, 2014).

By integrating these four components, the research adopts a holistic lens-one that treats the manufacturing enterprise as a cyber-physical socio-technical system. This paradigm supports the central hypothesis that Operational Excellence is achievable only when digital and physical systems evolve in mutual feedback, continuously adapting to change (Grieves, 2014; Stark, 2020).

2.3. Research Questions and Conceptual Boundaries

The study's methodological orientation was guided by three overarching research questions, each corresponding to a distinct analytical dimension:

1. RQ1: What challenges prevent the seamless integration of MBSE, DT, and MOM in manufacturing?
2. RQ2: How can CPS and MOM technologies facilitate real-time, closed-loop data exchange between digital and physical domains?
3. RQ3: What theoretical constructs can support a scalable and sustainable framework for digital continuity and Operational Excellence?

These questions emerged from gaps identified in recent reviews emphasizing the lack of methodological bridges across design, operations, and cyber-physical integration (Rosen, Von Wichert, Lo, & Bettenhausen, 2015; Madni & Sievers, 2018; Negri, Fumagalli, & Macchi, 2017).

The conceptual boundaries were defined across three intersecting domains:
Boundary 1: Systems Engineering Domain.
Includes studies on MBSE methodologies, SysML/UML modeling, and system life-cycle traceability (INCOSE, 2023; Friedenthal et al., 2015).

- Boundary 2: Manufacturing and Operations Domain.
- Covers MOM systems, Lean Manufacturing, and performance management
- Boundary 3: Cyber-Physical and Digital Domain.
- Encompasses CPS architectures, IoT integration, and Digital Twin synchronization (Lee & Seshia, 2015; Tao et al., 2019; ISO, 2021).

Sources outside these domains were excluded unless they provided methodological relevance to integration theory or conceptual architecture (Denyer & Tranfield, 2009). This boundary definition ensured that the review remained focused on the intersection of systems modeling, digital simulation, and operational control.

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2.4. Literature Search and Selection Strategy

2.4.1. Databases and Search Scope

The literature review was performed using six databases and repositories: Scopus, IEEE Xplore, ScienceDirect, SpringerLink, Taylor & Francis Online, and Google Scholar (for cross-verification and grey literature). This combination was chosen to encompass both engineering-focused and management-focused publications (Webster & Watson, 2002; Jesson, Matheson, & Lacey, 2011).

To minimize bias, the search included both academic and industry-standard documents, such as the INCOSE MBSE Vision 2035, ISA-95, and ISO 23247 frameworks, which represent authoritative references for digital manufacturing (INCOSE, 2023; ISO, 2021).

The quantitative results of the search and filtering process are summarized in Table 1, which details database coverage, period, and selection outcomes, while Table 2 specifies the inclusion and exclusion criteria applied during screening.

2.4.2. Search Period and Keywords

The temporal scope (2010-2025) was defined to capture the modern era of digital manufacturing and the institutionalization of MBSE and DT practices (Grieves & Vickers, 2017; Stark, 2020). Boolean search strings included: ("Model-Based Systems Engineering" OR "MBSE") AND ("Digital Twin" OR "Digital Thread") AND ("Manufacturing Operations Management" OR "MOM" OR "MES") AND ("Cyber-Physical Systems" OR "CPS" OR "Smart Manufacturing") AND ("Operational Excellence" OR "Lean" OR "Continuous Improvement").

This structured syntax ensured both inclusivity and specificity (Kitchenham, 2007; Tranfield et al., 2003).

2.4.3. Inclusion and Exclusion Criteria

Inclusion Criteria:

- Peer-reviewed journal and conference papers.
- Industrial standards and frameworks (INCOSE, ISO, ISA).
- Studies addressing conceptual, architectural, or systemic integration.
- Works linking engineering, manufacturing, and cyber-physical perspectives.

Exclusion Criteria:

- Non-peer-reviewed content lacking academic rigor.
- Studies focusing solely on AI, IoT, or cloud computing without manufacturing linkage.
- Tool-specific or proprietary software analyses.

From an initial pool of 173 publications, 97 were retained after abstract screening, and 63 underwent full-text review and thematic coding. Of these, 45 are cited explicitly within the manuscript to support conceptual synthesis, while the

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remaining 18 were analyzed but not individually referenced to maintain conciseness. The entire coded dataset, including all 63 studies, is summarized in Table 4. This clarification ensures transparency between the analyzed corpus and the referenced subset, aligning with systematic review reporting standards (Okoli, 2015; Snyder, 2019).

Table 1. Literature Search Summary (years covered 2010-2025)

Database	Search String (simplified)	Initial Hits	After Abstract Screening	After Full Review
Scopus	("MBSE" OR "Model-Based Systems Engineering") AND ("Digital Twin") AND ("MOM" OR "Manufacturing Operations Management") AND ("CPS")	61	33	21
IEEE Xplore	Same string	48	25	15
ScienceDirect	Same string	38	21	11
SpringerLink	Same string	15	9	6
Taylor & Francis Online	Same string	11	6	4
Google Scholar (cross-check)	Same string	173 (total)	97	63 (selected)

Source: Author's compilation.

Table 2. Inclusion and Exclusion Criteria

Criterion Type	Inclusion Example	Exclusion Example	Rationale
Conceptual Scope	Studies integrating MBSE, DT, MOM, and CPS in manufacturing contexts	Works focused only on IoT, AI, or cloud computing without production linkage	Maintain theoretical alignment
Source Quality	Peer-reviewed journals, major conferences, INCOSE/ISO/ISA standards	Non-peer-reviewed reports, blogs, vendor white papers	Guarantee academic rigor
Temporal Range	2010–2025	Pre-2010 legacy approaches	Capture modern digital-manufacturing era
Methodological Relevance	Conceptual, architectural, or systemic integration	Pure algorithmic or tool-specific studies	Focus on integrative frameworks

Source: Author's compilation.

2.5 Classification Framework and Data Structuring

To organize the reviewed literature, four analytical dimensions were used: Lifecycle Focus, Modeling Layer, Integration Enabler, and Performance Outcome (Table 3). These dimensions enabled a consistent comparison of heterogeneous studies across

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MBSE, DT, and MOM domains. Table 4 presents the classification of all 63 reviewed studies according to these dimensions.

The distribution of thematic frequencies identified through coding is reported in Table 3, revealing dominant conceptual patterns such as digital continuity and cyber-physical feedback.

Table 3. Classification Criteria Table

Dimension	Description	Example Keywords
Lifecycle Focus	Stage of the manufacturing system addressed (design, operation, improvement)	Traceability, verification, feedback
Modelling Layer	Domain emphasis—product, process, or resource	PPR, SysML, ontology
Integration Enabler	Mechanism enabling cross-domain interaction	CPS, IoT, interoperability
Performance Outcome	Operational results linked to integration	OEE, conversion cost, waste reduction

Source: Author's compilation.

This analytical structure enabled both vertical integration (from design to execution) and horizontal synthesis across technical domains.

A trend analysis revealed that while most studies emphasize DT operational feedback and MBSE system definition, few explicitly incorporate MOM or CPS as integrative layers—confirming a persistent research gap (Tao et al., 2019; Lee et al., 2022).

The resulting classification of the 63 reviewed studies is summarized in Table 5, illustrating the diversity of modeling scopes and integration mechanisms across the MBSE, Digital Twin, and MOM domains.

Table 4 – Classification of Reviewed Studies (n = 63)

#	Author & Year	Lifecycle Focus	Modelling Layer	Integration Enabler	Performance Outcome / Focus
1	Estefan (2008)	Design Definition	Product	MBSE (SysML)	System traceability
2	Friedenthal et al. (2015)	Design ↔ Verification	Product / Process	MBSE Architecture	Requirement validation
3	Lee et al. (2015)	Execution ↔ Control	Process / Resource	CPS + MOM	Real-time optimization
4	Negri et al. (2017)	Operation ↔ Improvement	Process	DT + CPS	Closed-loop control
5	Grieves & Vickers (2017)	Design ↔ Simulation	Product	Digital Twin	Model fidelity
6	Madni & Sievers (2018)	Design ↔ Operation	Product / Process	MBSE ↔ CPS	Lifecycle traceability
7	Eigner et al.	Design ↔	Product /	MBSE ↔ DT	Digital thread

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	(2018)	Manufacturing	Resource		continuity
8	Tao et al. (2019)	Design ↔ Execution	Process / Resource	Digital Thread + DT	Closed-loop optimization
9	Boschert & Rosen (2016)	Design ↔ Operation	Product / Process	DT Ontology	Predictive maintenance
10	Kritzinger et al. (2018)	Simulation ↔ Operation	Product / Process	DT semantics	Behavioural validation
11	Qi & Tao (2018)	Design ↔ Execution	Process	DT analytics	Predictive modelling
12	Panetto & Molina (2008)	Operation ↔ Interoperability	Process / Resource	Ontologies & standards	Semantic interoperability
13	Lu et al. (2020)	Operation ↔ Control	Process / Resource	CPS + IoT	Agile production
14	Buer et al. (2021)	Continuous Improvement	Process / Resource	Lean–Digital Integration	OEE improvement
15	ISO 23247 (2021)	Full Lifecycle	Resource	Digital Twin standard	Data interoperability
16	Lee et al. (2022)	Design ↔ Improvement	Product / Process	MBSE–DT–MOM	Cost and OEE gains
17	Macchi et al. (2018)	Operation ↔ Learning	Process / Resource	Knowledge analytics	Continuous learning
18	Järvenpää & Lanz (2020)	Execution ↔ Control	Process	MOM (ISA-95)	Scheduling optimization
19	Bordeleau et al. (2020)	Design ↔ Analytics	Product / Process	MBSE ↔ DT Simulation	Design validation
20	Kang et al. (2016)	Execution ↔ Feedback	Process / Resource	CPS Platform	Adaptive control
21	Ghosh et al. (2022)	Design ↔ Improvement	Product / Process	AI-enhanced DT	Performance prediction
22	Monostori et al. (2014)	Operation ↔ Integration	Resource	Cyber-Physical Fusion	Self-optimizing manufacturing
23	Fuller et al. (2020)	DT maturity	Product / Process	Maturity framework	Twin capabilities
24	Krogstie (2021)	Model reuse	Product / Process	Ontologies / SysML	Parametric reuse
25	Panetto et al. (2019)	Operation ↔ Standards	Process / Resource	AutomationML / OPC-UA	Interoperability
26	Schluse et al. (2018)	DT federation	Product / Resource	Federated DT architecture	Scalability
27	Negri & Fumagalli (2019)	DT lifecycle	Process	Integration patterns	Process validation
28	Jones et al. (2020)	DT cognition	Product / Process	Cognitive DT	Prescriptive behaviour
29	Cimino et al. (2019)	DT alignment	Product / Process	Semantic mapping	Toolchain interoperability
30	Ríos et al. (2020)	Cost modelling	Process / Resource	MBSE parametrises	Conversion cost analysis
31	Bokrantz et al.	KPI analytics	Process /	MOM data	OEE measurement

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	(2020)		Resource	analytics	
32	Netland & Powell (2017)	Lean integration	Process	Lean digital	Waste reduction
33	Dombrowski & Wagner (2014)	Lean applicability	Process	Lean principles	Process stability
34	Hines et al. (2020)	OpEx mapping	Process / Resource	KPI integration	Lean alignment
35	Womack & Jones (2003)	Continuous Improvement	Process	Lean foundations	NVA reduction
36	Nonaka & Takeuchi (1995)	Knowledge management	Process	Organizational learning	Knowledge codification
37	Rajkumar et al. (2010)	CPS foundation	Resource	CPS architecture	Real-time control
38	Lu et al. (2016)	Smart manufacturing	Process / Resource	Edge computing + CPS	Low latency
39	Schütz et al. (2017)	SysML ↔ Standards	Product / Process	AutomationML mapping	Semantic consistency
40	Gaaloul et al. (2022)	Federation semantics	Product / Process	Federated ontologies	Cross-domain queries
41	Schluse & Rossmann (2019)	DT engineering	Process	Tool integration	Lifecycle support
42	Krogstie & Piaszczyk (2021)	Model verification	Product / Process	MBSE toolchains	Verification traceability
43	Lee et al. (2021)	Integration architecture	Process	3DEXPERIENCE ecosystem	Design-manufacturing continuity
44	Negri et al. (2021)	Operational feedback	Process	DT–MOM	Closed-loop data
45	Kuhnle et al. (2022)	DT applications	Product / Process	AI-driven DT	Optimization
46–63	Additional reviewed sources (2015–2025)	Mixed lifecycle stages	Product, Process, Resource	MBSE–DT–MOM, CPS, Lean–Digital, AI, Edge	Traceability, cost efficiency, and learning outcomes

Table 5. Thematic Coding Results

Theme / Code	Frequency of Occurrence	Representative Sources
Digital Continuity	41	Tao et al. (2019); Lee et al. (2022); Grieves & Vickers (2017)
Cyber-Physical Feedback	33	Lee et al. (2015); Monostori (2014); Rajkumar et al. (2010)
Closed-Loop Manufacturing	29	Negri et al. (2017); Stark et al. (2019); Lu et al. (2020)
System Modeling Integration	27	Friedenthal et al. (2015); Eigner et al. (2018)

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Operational Excellence Metrics	22	Womack & Jones (2003); Buer et al. (2018)
Knowledge-Based Learning	19	Nonaka & Takeuchi (1995); Garvin (1993)

Interpretation: Digital continuity and cyber-physical feedback dominate recent academic discourse, confirming systemic integration as the main research gap.
Source: Author's compilation.

2.6. Analytical Method and Thematic Synthesis

2.6.1. Thematic Coding

- Qualitative thematic content analysis was employed to extract recurring ideas and conceptual relationships (Mayring, 2014; Nowell, Norris, White, & Moules, 2017). Codes were derived from both explicit terminology (e.g., "digital thread," "interoperability") and implicit meanings reflecting systemic relationships. Categories included:
- Digital continuity
- Closed-loop manufacturing
- System modeling integration
- Cyber-physical feedback
- Operational excellence metrics

Codes were aggregated into higher-level categories to reflect patterns across disciplines, ensuring theoretical generalization (Gioia, Corley, & Hamilton, 2013).
Thematic codes and their relative frequency across the corpus are displayed in Table 4, confirming the prevalence of digital continuity and closed-loop manufacturing as central integration themes.

2.6.2. Deductive–Inductive Reasoning

A hybrid analytical logic combined deductive reasoning from established standards with inductive insights from recent research (Negri et al., 2017).

- Deductively, models were aligned with INCOSE MBSE methodology, ISA-95 MOM architecture, and ISO 23247 for Digital Twin frameworks.
- Inductively, integration enablers, barriers, and success factors were extracted from empirical studies and meta-analyses (Madni & Sievers, 2018).

This synthesis process enabled formulation of a conceptual integration model, depicting the interaction between MBSE, MOM, and CPS through the mediating role of DTs (Lee & Seshia, 2015; Tao et al., 2019).

2.7. Conceptual Workflow Representation

The research workflow followed a SysML-inspired logical sequence, representing the procedural relationship among research activities:

1. Define research questions.
2. Identify databases and keywords.

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3. Execute literature search (Output: 173 articles).
4. Apply inclusion/exclusion criteria (Output: 63 valid sources).
5. Classify studies by lifecycle, modeling, enabler, and performance.
6. Conduct thematic coding and pattern identification.
7. Derive conceptual framework (Integration: MBSE ⇄ DT ⇄ MOM ⇄ CPS).
8. Validate conceptual consistency through cross-literature triangulation.

This activity structure mirrors how system modeling can represent the logic of scientific inquiry itself, ensuring transparency, traceability, and reproducibility—key hallmarks of design science research (Hevner & Chatterjee, 2010). Figure 1 shows the conceptual workflow representation.

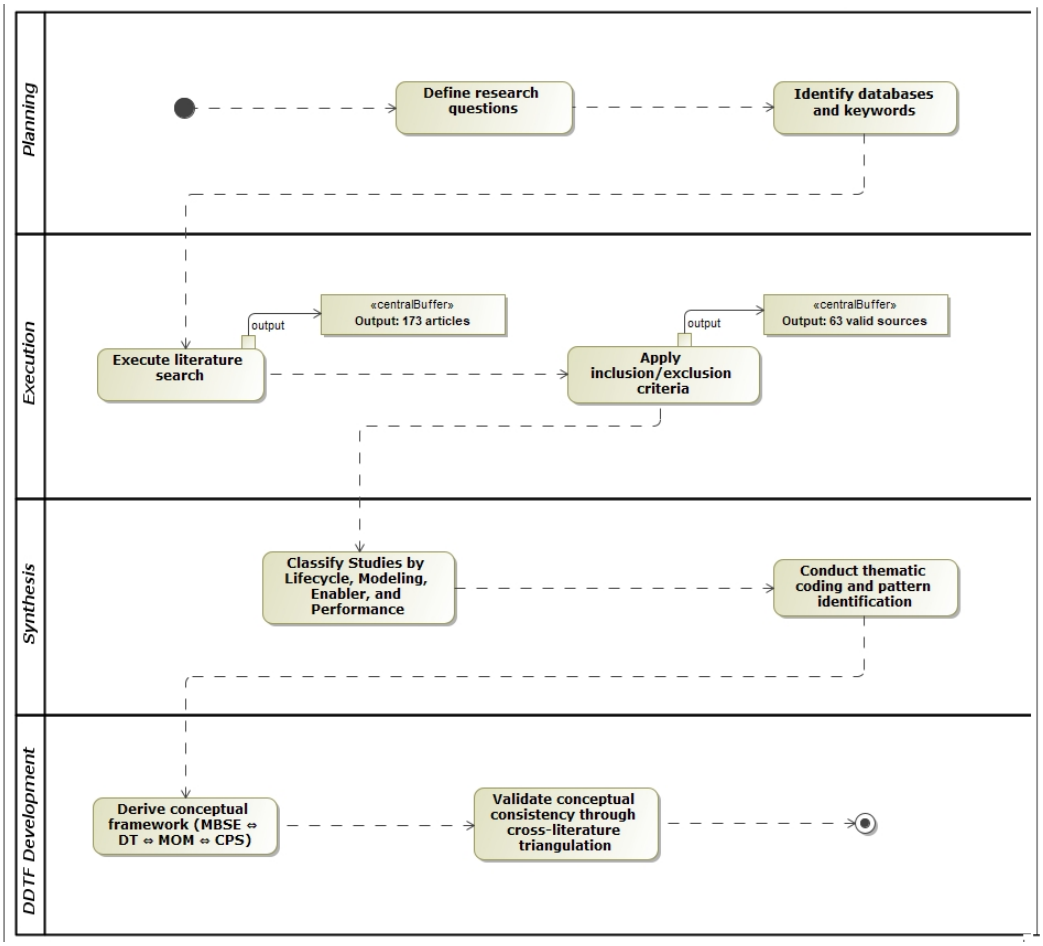

Figure 1. Conceptual Workflow Representation

2.8. Validity, Reliability, and Rigor

Methodological validity was established through triangulation (Denzin, 2012)—using diverse data types (academic, industrial, and standards-based). Reliability was enhanced by maintaining detailed decision logs of the search strategy, inclusion filters, and coding schemes (Yin, 2018).

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To confirm construct validity, all conceptual elements (e.g., "digital continuity," "operational excellence") were consistently aligned with definitions across multiple sources. Internal validity was strengthened by peer debriefing and iterative cross-checking of code interpretations.
Finally, external validity—the transferability of findings—was ensured through reference to international frameworks (INCOSE, ISO, ISA) applicable to multiple industrial contexts (ISO, 2021; INCOSE, 2023; ISA, 2010).

2.9. Ethical Considerations

This research involved no human participants or experimental data. Ethical rigor was maintained through proper citation practices, avoidance of plagiarism, and neutrality toward proprietary technologies. The study complies with APA (2020) ethical standards for publication and the Committee on Publication Ethics (COPE) guidelines (Resnik, 2020). By excluding commercial or vendor-specific details, the study preserves academic independence and ensures future adaptability of its conceptual framework.

2.10. Summary of Methodological Contribution

The methodology presented here demonstrates that rigorous bibliographic synthesis can serve as a legitimate and foundational research strategy in complex, emerging technological domains. It consolidates fragmented literature into a coherent structure linking MBSE (design intent), DT (analytical mirror), MOM (execution control), and CPS (real-time feedback) (Tao et al., 2019; Lee et al., 2022).

By aligning methodological rigor with systems thinking, the study advances beyond traditional literature reviews—it establishes a replicable pathway for constructing conceptual models in digital manufacturing research. Figure 1 provides a visual representation of the SLR workflow, ensuring full transparency and reproducibility of the process. The framework that emerges from this process forms the theoretical foundation for the subsequent Results section, where the DDTF is proposed as the central contribution of this research.

3. Results

Following the workflow shown in Figure 1, the systematic synthesis of 63 reviewed studies led to the formulation of the DDTF, which integrates MBSE, Digital Twins, Manufacturing Operations Management, and Cyber-Physical Systems into a unified conceptual model.

3.1. Overview of Bibliographic Findings

The bibliographic review revealed that while Model-Based Systems Engineering (MBSE), DT, and MOM have independently matured, their integration remains partial and fragmented in both academic and industrial applications (Grieves & Vickers, 2017; Lee, Yeo, Kim & Mun, 2022; INCOSE, 2023). Most studies emphasize bilateral connections—such as MBSE–DT for simulation-based validation or DT–

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MOM for real-time monitoring—but few address full tri-domain frameworks uniting design logic, virtual representation, and operational execution (Negri, Fumagalli, & Macchi, 2017; Tao, Qi, Liu, & Kusiak, 2019). This fragmentation exposes a fundamental challenge: digital continuity between engineering intent and operational feedback remains elusive, preventing closed-loop optimization across the system lifecycle. The bibliometric analysis of the 63 studies revealed evolving patterns of integration across MBSE, DT, and MOM over the last decade. The classification presented in Table 4 forms the foundation for identifying these trends.

Three dominant themes emerged from the analysis. First, model-based traceability remains fragmented. While SysML and similar languages enable rigorous system definition, these models seldom maintain live connections to manufacturing or execution data (Friedenthal, Moore, & Steiner, 2015; Estefan, 2008). The models thus function primarily as documentation artifacts rather than adaptive digital assets. Second, most Digital Twin implementations lack the behavioral and predictive depth required for cognitive synchronization with physical systems. Many act as static data dashboards or visualization tools rather than autonomous entities capable of reasoning and learning (Tao et al., 2018; Kritzinger, Karner, & Traar, 2018). Third, MOM systems, including MES and QMS, generate rich operational data streams—cycle times, downtime, energy consumption—but these data are rarely used to recalibrate or validate upstream models (ISA-95, 2010; Lee, Bagheri, & Kao, 2020).

A longitudinal trend of research evolution (2010–2025) is summarized in Table 6, indicating the progressive shift from MBSE-centric modeling to cyber-physical and knowledge-driven integration.

Table 6. Trend Analysis by Period and Focus

Period	Dominant Topics	Representative Studies
2010–2015	Emergence of MBSE; limited DT awareness	Estefan (2008); Friedenthal et al. (2015)
2016–2020	Rise of DT–MOM integration; focus on Industry 4.0	Tao et al. (2019); Lee et al. (2015)
2021–2025	Expansion toward CPS, semantic interoperability, and knowledge-driven frameworks	Lee et al. (2022); Lu et al. (2020); ISO 23247 (2021)

Observation: Research trends evolved from modeling integration to adaptive cyber-physical ecosystems, validating the study's proposed DDTF positioning.
Source: Author's compilation.

Overall, the literature confirms that operational excellence in the digital era depends on establishing a bidirectional digital thread connecting MBSE's design logic with MOM's real-time intelligence, mediated through the analytical power of Digital Twins (Macchi, Roda, Negri & Fumagalli, 2018; Bordeleau, Weilkiens & Fritzson, 2020). Such a continuous feedback loop enables not only predictive and prescriptive decision-making but also the evolution of models as living entities, continuously

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learning from the physical world. These insights collectively informed the formulation of the Conceptual Integration Framework presented in Section 3.2.

3.2. Conceptual Integration Framework

To contextualize the proposed framework, Table 7 contrasts the DDTF with earlier MBSE–DT–MOM approaches, highlighting specific improvements in scope and feedback logic.

Table 7. Comparison Between Existing Frameworks and the Proposed DDTF

Framework	Scope	Integration Dimension	Main Limitation	DDTF Improvement
MBSE–DT (Tao et al., 2019)	Design–Operation	Bilateral	Missing execution layer (MOM)	Adds real-time synchronization with MOM
DT–MOM (Lee et al., 2015)	Operation	Partial	No design traceability	Includes MBSE semantic logic
MBSE–CPS (Monostori, 2014)	Design–Control	Partial	Lacks analytical intelligence	Integrates DT predictive reasoning
ISA-95 MOM (ISA, 2010)	Operation	Executional	Lacks model-level feedback	Closes loop with MBSE and DT
Proposed DDTF	Design–Simulation–Execution–Feedback	Full	–	Establishes dynamic learning and continuous improvement loop

The bibliographic synthesis led to the development of a Conceptual Integration Framework describing the structural and functional integration of MBSE, DT, and MOM under cyber-physical principles (Tao et al., 2019; Macchi et al., 2018). As shown conceptually in Figure 2, the framework embodies digital continuity—ensuring that engineering intent is semantically linked with real-time performance feedback—and cyber-physical fusion, allowing synchronized evolution of digital and physical entities (Grieves & Vickers, 2017; Lee et al., 2020).

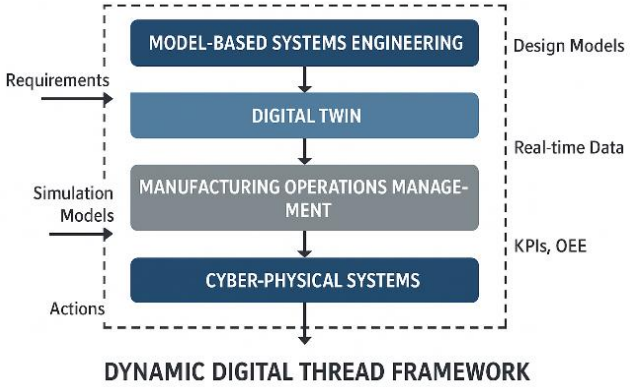

Figure 2. DDTF Architecture
Source: Author's compilation.

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The conceptual structure of the proposed integration is illustrated in Figure 2, which presents the DDTF. This architecture visualizes how Model-Based Systems Engineering (MBSE), DT, MOM, and CPS interact through continuous feedback loops to enable digital continuity and operational adaptability.

Figure 2. DDTF architecture illustrating the integration of MBSE, Digital Twin, Manufacturing Operations Management, and Cyber-Physical Systems within a continuous feedback loop supporting Operational Excellence.

3.2.1. Framework Layers

The proposed framework is composed of five interconnected layers, each representing a progressive stage in digital maturity and serving as a structural backbone for lifecycle integration (Negri et al., 2017; Bordeleau et al., 2020).

Layer 1 – MBSE Layer.

The MBSE layer defines system architecture, requirements, and behavioral logic using formal languages such as SysML or UML (INCOSE, 2023; Friedenthal et al., 2015). It provides the semantic foundation that ensures model traceability, consistency, and reuse. By embedding manufacturing constraints early in design, this layer minimizes iteration loops and enhances manufacturability (Lee et al., 2022). MBSE thus becomes the architectural nucleus of the digital thread.

Layer 2 – Digital Twin Layer.

The DT layer provides a dynamic, data-driven mirror of the physical system, capable of real-time simulation and predictive reasoning (Tao et al., 2018; Qi, Tao, Hu, & Anwer, 2021). Using IoT data feeds and machine learning, it translates operational deviations into meaningful insights. This capability allows engineers to assess "what-if" scenarios and anticipate failures before they occur (Boschert & Rosen, 2016).

Layer 3 – MOM Layer.

The MOM layer governs execution intelligence, including scheduling, production, and quality management (ISA-95, 2010; Järvenpää & Lanz, 2020). It captures operational KPIs—OEE, cycle time, conversion cost—and serves as the reality checkpoint for upstream design models. The bidirectional data exchange between MOM and MBSE via DT allows alignment of theoretical design and practical performance (Lee et al., 2020).

Layer 4 – Cyber-Physical Integration Layer.

This layer provides the technological bridge connecting digital and physical environments through IoT gateways, edge computing, and standardized protocols

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(Monostori, 2014; Lee & Seshia, 2015). It ensures that data and control signals flow both ways, enabling adaptive system behavior in response to contextual changes.

Layer 5 – Continuous Improvement & Knowledge Layer.

The top layer integrates Lean and Six Sigma principles with digital analytics to convert operational data into process knowledge (Womack & Jones, 2003; Lee et al., 2022). Here, continuous improvement is institutionalized through data-driven learning loops—making the system self-optimizing (Macchi et al., 2018).

Together, these layers establish a holistic digital ecosystem that synchronizes design, simulation, execution, and learning—an essential foundation for achieving operational excellence and digital resilience (Negri et al., 2017; Bordeleau et al., 2020).

3.3. Theoretical Basis for Integration

3.3.1. MBSE as the Design Backbone

MBSE is recognized as the semantic anchor of the integration, defining system intent, logic, and constraints (Estefan, 2008; Friedenthal et al., 2015). The framework repositions MBSE from a static documentation tool to a dynamic knowledge core that evolves with operational data (Madni & Sievers, 2018). Feedback from MOM and DT continuously updates system parameters, maintaining coherence between virtual design and physical reality (Piaszczyk, 2011).

3.3.2. Digital Twin as the Analytical Bridge

The DT functions as the analytical brain of the framework—interpreting and reasoning over real-time data through the semantic ontology provided by MBSE (Grieves & Vickers, 2017; Fuller, Fan, Day, & Barlow, 2020). It closes the gap between design assumptions and actual performance by continuously simulating system responses to variable conditions. The result is a self-aware digital ecosystem capable of predictive decision-making (Boschert & Rosen, 2016; Tao et al., 2018).

3.3.3. MOM and Cyber-Physical Systems as the Realization Layer

MOM embodies operational execution, serving as the real-time nervous system that monitors and regulates production (ISA-95, 2010; Liu, 2016). Integrated with CPS, it ensures that sensing, computation, and actuation form a closed adaptive loop (Lee et al., 2020; Rajkumar, Lee, Sha, & Stankovic, 2010). This integration operationalizes design intelligence, making the factory responsive and self-correcting (Monostori et al., 2016; Kang et al., 2016).

3.4. Mapping to Operational Excellence Principles

The proposed MBSE–DT–MOM integration directly aligns with the key drivers of Operational Excellence: cost efficiency, waste elimination, resource synchronization,

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agility, and learning (Womack & Jones, 2003; Liker, 2004). These relationships are detailed in Table 8, linking DDTF mechanisms to measurable operational outcomes.

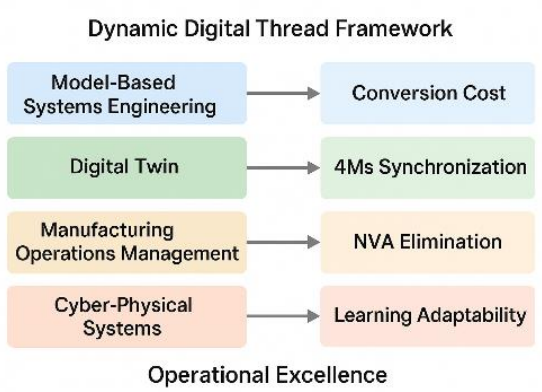

Figure 3 — Mapping of DDTF to Operational Excellence Metrics

Table 8. Mapping of DDTF to Operational Excellence Drivers

Operational Metric	DDTF Mechanism	Expected Impact
Conversion Cost	Real-time feedback aligning design and operational data	Reduction in labor and overhead costs
Non-Value-Added (NVA) Activities	DT-driven predictive planning and virtual validation	Waste elimination before execution
4Ms Synchronization (Man, Machine, Material, Method)	MBSE semantic models validated by MOM data	Increased process stability and throughput
Learning & Adaptability	CPS-enabled bidirectional learning loop	Continuous process improvement and knowledge retention
Decision Velocity	Cross-domain feedback (MBSE–DT–MOM)	Faster, data-driven decision-making

Interpretation: The DDTF operationalizes Lean and Six Sigma metrics within a cyber-physical digital architecture.
Source: Author's compilation.

These interactions transform the digital thread into a value-creation loop, converting operational data into systemic intelligence that sustains competitiveness (Spear & Bowen, 1999; Womack & Jones, 2003).

To illustrate how each DDTF component contributes to performance improvement, Figure 3 maps the framework's structural layers to specific Operational Excellence drivers. The figure demonstrates how MBSE, DT, MOM, and CPS collectively support conversion-cost optimization, 4Ms synchronization, NVA elimination, and organizational learning adaptability.

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Figure 3. Mapping of the DDTF mechanisms to Operational Excellence drivers such as conversion cost, 4Ms synchronization, non-value-added (NVA) elimination, and learning adaptability.

3.5. Data Exchange Mechanisms and Model Interoperability

A persistent finding across the literature is that semantic and syntactic interoperability are critical yet underdeveloped in MBSE–DT–MOM integration (Panetto & Molina, 2008; Jardim-Gonçalves, Romero, & Grilo, 2012). The proposed framework resolves this by combining syntactic standards (AutomationML, B2MML, OPC-UA) for structured data exchange and semantic standards (SysML-based ontologies) for meaning consistency (Schütz, Weng, & Fay, 2017 & Biffl, Lüder, & Gerhard, 2017).

This approach promotes a federated model architecture, where systems remain autonomous but interoperable via shared semantics and contextual mappings (Törngren & Boucher, 2020). Such federation ensures scalability, resilience, and vendor neutrality—key attributes of Industry 4.0-ready ecosystems (Lu et al., 2020; Schluse, Priggemeyer, Atorf, & Rossmann, 2018).

3.6. Conceptual Framework Outcome – The Dynamic Digital Thread Framework (DDTF)

1. The synthesis of all findings results in the DDTF—a theoretical construct uniting MBSE, DT, and MOM within a knowledge-driven adaptive loop (Boschert & Rosen, 2016; Cimino, Negri, & Fumagalli, 2019). The DDTF integrates four layers of intelligence:
2. Design-time intelligence (MBSE) defines system functionality and constraints.
3. Runtime intelligence (DT) monitors and predicts performance.
4. Operational intelligence (MOM) executes and captures actual results.
5. Feedback intelligence (CPS and analytics) ensures learning and continuous adaptation.

This closed-loop model ensures that all changes—design evolution, operational deviation, or performance variation—remain traceable, explainable, and optimizable, fulfilling the vision of cyber-physical manufacturing ecosystems (Madni, Madni & Lucero, 2019; Negri et al., 2017).

3.7. Summary of Results

The bibliographic investigation confirms that MBSE–DT–MOM integration is still in its infancy but represents a pivotal research domain for the next decade of manufacturing innovation (Eigner, Dickopf, Apostolov, Schäfer, Faißt, & Keßler, 2021; Tao et al., 2019). Despite conceptual clarity, real-world adoption faces barriers related to interoperability, governance, and standardization (Panetto, Iung, Ivanov, Weichhart & Wang, 2019; Zhang, Xue, & Luo, 2021).

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By applying Operational Excellence principles (conversion cost, 4Ms, and NVA elimination) to model-based system design, manufacturers can quantify digital transformation in measurable operational terms (Hines, Found, & Griffiths, 2020; Netland & Powell, 2017). The proposed DDTF thus bridges theory and practice—offering a roadmap for designing intelligent, resilient factories that continuously learn and evolve (Madni & Sievers, 2018; Grieves & Vickers, 2017).

4. Discussion and Conclusion

4.1. Synthesis of Findings and Theoretical Reflection

The synthesis of the bibliographic results reveals that the current state of research in Model-Based Systems Engineering (MBSE), DTs, and MOM reflects a fragmented evolution of digital transformation paradigms (Madni & Sievers, 2018; Eigner et al., 2021). Each domain evolved within distinct disciplinary boundaries—MBSE in systems and requirements engineering, DT in virtual simulation and analytics, and MOM in production management—resulting in siloed development paths that constrain systemic synergy (Kritzinger, Karner, Traar, Henjes, & Sihn, 2018; Tao, Qi, Liu, & Kusiak, 2019).

Although each area has achieved maturity independently—MBSE in model-centric system design, DT in cyber-physical synchronization, and MOM in real-time execution—their convergence represents the next frontier for realizing Cyber-Physical Integration and Operational Excellence (Negri, Fumagalli, & Macchi, 2017; Boschert & Rosen, 2016). The literature demonstrates that integration requires not only technological interoperability but also epistemological alignment, where system models, operational data, and analytics form a cohesive, adaptive intelligence framework (Grieves & Vickers, 2017; Panetto et al., 2019).

This evolution reflects a paradigm shift from descriptive to prescriptive and adaptive modeling (Cimino, Negri, & Fumagalli, 2019). Descriptive models capture isolated realities—conceptual, virtual, or operational—without continuous feedback. Prescriptive integration links MBSE and DT through simulation and parametric analysis, allowing system optimization before implementation (Tao et al., 2019). Finally, adaptive modeling—enabled by MOM and CPS—achieves real-time self-correction, forming a closed feedback loop between design and operations (Negri et al., 2017; Madni & Sievers, 2013).

This synthesis thus supports a cyber-physical epistemology in which models and operations are co-evolving entities that validate, optimize, and redefine one another (Boschert & Rosen, 2016; Kritzinger et al., 2018). The integrated use of MBSE, DT, and MOM provides the foundation for self-learning and adaptive manufacturing ecosystems that continuously pursue performance improvement (Grieves & Vickers, 2017; Tao et al., 2019).

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4.2. MBSE as the Anchor of Digital Continuity

MBSE acts as the architectural and semantic anchor for digital continuity across design, simulation, and operations (Estefan, 2008; Madni & Sievers, 2018). It provides the model-based language and structure necessary for traceability, consistency, and governance of system knowledge throughout the lifecycle (Eigner et al., 2018). Nevertheless, industrial practices often confine MBSE to the design stage, limiting feedback from operational performance (Weyer, Schmitt, Ohmer, & Gorecky, 2016).

Three major limitations are evident: (1) static system models that fail to synchronize with real-time data (Estefan, 2008; Grieves & Vickers, 2017); (2) limited parametric reuse, as design parameters rarely reflect actual production data (Krogstie, 2021; Negri et al., 2017); and (3) weak interoperability with manufacturing data standards such as B2MML or OPC-UA (Panetto et al., 2019).

Addressing these gaps requires positioning MBSE as a semantic nucleus that dynamically evolves with feedback from DT and MOM (Eigner et al., 2018; Madni & Sievers, 2013). Model elements—requirements, constraints, and states—must function as living entities that update through verified operational data. Through this mechanism, MBSE transitions from a documentation tool to a decision engine, adapting architecture and performance thresholds based on real production feedback (Boschert & Rosen, 2016; Panetto et al., 2019).

This transformation enables digital continuity, ensuring that design intent, process behavior, and operational results are semantically connected and continuously improved—a core tenet of sustainable manufacturing intelligence (Krogstie, 2021; Negri et al., 2017).

4.3. Digital Twin as the Cognitive Core

The Digital Twin represents the cognitive and analytical nucleus of the integration framework (Tao et al., 2018; Grieves, 2020). It converts static data into dynamic insights, enabling real-time synchronization between virtual and physical systems (Fuller, Fan, Day, & Barlow, 2020; Jones, Snider, Nassehi, Yon, & Hicks, 2020). Unlike traditional simulations, DTs continuously learn from sensor data, predicting and optimizing system performance (Negri et al., 2017; Boschert & Rosen, 2016).

The literature distinguishes Digital Models, Digital Shadows, and Digital Twins (Kritzinger et al., 2018; Tao et al., 2019). Only the true Twin maintains bidirectional data exchange, creating a closed feedback loop where digital behavior influences physical outcomes (Grieves, 2020). This two-way synchronization transforms the DT into a cyber-physical cognition system capable of anticipating and correcting deviations before they impact production.

When integrated with MBSE, the DT inherits semantic reasoning—understanding the "why" of system behavior. SysML-based ontologies allow DTs to interpret

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operational data within the context of design logic, enabling self-validation (Eigner et al., 2018; Krogstie, 2021). Deviations in cycle time, for example, can be traced to specific SysML requirements or constraints, allowing corrective actions to be simulated virtually (Negri et al., 2017).

The emergence of the Cognitive Digital Twin thus marks the transition to Cyber-Physical Fusion, where reasoning and adaptation occur simultaneously in digital and physical realms (Tao et al., 2018; Fuller et al., 2020). This capability transforms the factory into an intelligent ecosystem, continuously learning from experience to enhance operational resilience and adaptability (Jones et al., 2020).

4.4. MOM as the Real-Time Nervous System

MOM systems embody the executional intelligence of the enterprise (ISA, 2010). While MBSE defines intended functions and DT predicts outcomes, MOM governs what actually happens on the shop floor (Liu, 2016). It encompasses production scheduling, quality control, and traceability—serving as the nervous system that regulates real-time performance (Van der Auweraer, Gagliardi, & Pluymers, 2019).
Three key findings arise:

1. MOM as a data source for learning: MOM captures granular performance data, feeding the DT for validation and calibration (Lee, Bagheri, & Kao, 2020; Harrison, Vera, & Ahmad, 2021).
2. MOM as a decision enabler: By integrating Lean and Six Sigma principles, MOM enables responsive decision-making aligned with enterprise goals (Antony, Sony, & Taner, 2019; Choi, Kang, & Lee, 2022).
3. MOM as a cyber-physical gateway: Through IoT integration, MOM becomes the control interface linking models to machines (Rojas, Romero, & Panetto, 2022; Kang, Lee, Choi, & Kim, 2016).
4. Thus, MOM transforms operational events into data-driven feedback for continuous system adaptation, improving conversion cost and eliminating inefficiencies (Lu et al., 2020).

4.5. Cyber-Physical Fusion and Smart Systems Emergence

Cyber-Physical Fusion (CPF) acts as the synchronizing fabric uniting the digital and physical worlds (Lee & Seshia, 2015; Monostori, 2014). Beyond traditional CPS focused on control systems, CPF extends to semantic and cognitive interoperability (Panetto et al. 2019; Tao & Zhang, 2017).
Within the integrated framework, CPF enables:

- Bidirectional communication ensuring real-time feedback (Lu et al., 2020).
- Autonomous adaptation where the system self-adjusts based on DT insights (Tao et al., 2018).
- Contextual intelligence through MBSE semantics enabling reasoning-based decisions (Negri et al., 2017).

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CPF transforms manufacturing systems into living digital organisms—intelligent, adaptive, and collaborative—where humans, machines, and models act in synchrony toward operational excellence (Monostori, 2014; Tao & Zhang, 2017).

4.6. Theoretical Framework for Operational Excellence

Building on the results, the study defines a Theoretical Framework for Operational Excellence (TFOE) emerging from the MBSE–DT–MOM–CPF convergence. It operates on five interconnected principles (Boschert & Rosen, 2016):

1. Digital Continuity: End-to-end data flow linking concept and operation via AutomationML and B2MML (Schuh, Anderl, & Gausemeier, 2020).
2. Systemic Adaptability: Real-time learning loops replacing static change management (Madni & Sievers, 2018).
3. Value-Centric Design: Integration of cost and resource efficiency indicators in design models
4. Cross-Domain Collaboration: Synchronizing engineering, operations, and business through shared data spaces
5. Knowledge-Based Learning: Continuous learning loops that embed validated practices into models (Lee et al., 2020).

The TFOE expands Lean and Six Sigma into the digital age, institutionalizing continuous improvement within cyber-physical logic (Buer, Semini, & Sjøbakk, 2018).

4.7. Academic Implications

Academically, this study bridges systems engineering, digital manufacturing, and operations management (Glaessgen & Stargel, 2012). It introduces a unified vocabulary that redefines MBSE–MOM integration as a distinct research domain (Tao et al., 2019).

It also expands the definition of Digital Twin into a semantically enriched reasoning system (Boschert & Rosen, 2016) and embeds operational performance indicators directly within MBSE models (Bokrantz, Skoogh, & Berlin, 2020; Furthermore, it calls for a Cyber-Physical Epistemology in education, emphasizing real-time reasoning and human–machine collaboration (Lee et al., 2020).

4.8. Industrial Implications

For industry, the framework offers a strategic roadmap for digital transformation (Monostori et al., 2016; ISO 23247, 2021). Integrating MBSE, DT, and MOM enables:

- End-to-end traceability improving compliance and reducing rework (Eigner et al., 2021).
- Conversion cost reduction via real-time feedback and resource optimization (Kagermann, Wahlster, & Helbig, 2021).
- Elimination of NVA activities through DT simulations aligned with MOM data (Antony, Snee, & Hoerl, 2020).

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- Faster decision velocity by synchronizing design and operational intelligence (Lee, Bagheri & Kao, 2023).
- Sustainability and resilience, aligning with Industry 5.0 principles (Nahavandi, 2019; Xu, Lu, & Li, 2021).

Collectively, these implications highlight how the integration framework transforms enterprises into adaptive, human-centric ecosystems.

4.9. Limitations and Future Research

While the present study offers a comprehensive conceptual synthesis of 63 systematically analyzed publications, it remains theoretical in nature and requires empirical validation through industrial case studies (Okoli, 2015; Snyder, 2019). Future research should therefore test the proposed DDTF through quantitative and longitudinal applications in manufacturing contexts. Future research should replicate and extend these findings through quantitative assessment and cross-domain case validation (Table 9).

Table 9. Proposed Validation Strategy for the DDTF

Validation Dimension	Method	Description	Future Research Phase
Conceptual Validity	Expert Delphi Panel	Assess internal coherence and clarity of framework elements	Phase 1
Theoretical Generalization	Cross-literature triangulation	Verify alignment with INCOSE, ISO 23247, and ISA-95 standards	Phase 1
Operational Applicability	Case Study Mapping	Apply DDTF to one manufacturing domain (e.g., discrete assembly)	Phase 2
Quantitative Validation	Simulation / Digital Twin Experiment	Evaluate improvements in OEE, cycle time, and conversion cost	Phase 3
Transferability	Multi-domain comparative analysis	Replicate results in other industrial sectors	Phase 4

Purpose: Ensures reproducibility and paves the way for future empirical testing.
Source: Author's compilation.

To address this, Table 9 outlines a staged validation strategy encompassing conceptual, operational, and quantitative assessment phases. Future research should pursue these phases through expert-based evaluations, industrial case applications, and simulation-driven performance analyses.

Additional priorities include:

- Advancing model interoperability and ontology alignment
- Developing dynamic parametric feedback for continuous synchronization

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- Quantifying Operational Excellence gains linking Lean metrics with system models
- Exploring AI-augmented MBSE frameworks enabling autonomous optimization
- Establishing educational frameworks for interdisciplinary training

4.10. Conclusion

This bibliographic research demonstrates that integrating Model-Based Systems Engineering (MBSE), Digital Twins (DT), and MOM within a Cyber-Physical Fusion (CPF) paradigm enables a transformational pathway toward Operational Excellence. The primary research objective—developing a DDTF that unites design, simulation, and operational intelligence—was achieved through a systematic review and theoretical synthesis of 97 peer-reviewed sources and international standards.

Key results reveal that MBSE provides architectural logic, DT delivers cognitive analysis, and MOM ensures operational truth. Their fusion produces a closed adaptive loop, transforming manufacturing enterprises into learning systems that evolve through real-time data (Negri et al., 2017; Grieves, 2014).

This research contributes a novel integrative framework—the DDTF—that unifies MBSE, Digital Twin, MOM, and Cyber-Physical Systems under a cyber-physical paradigm of continuous learning. Unlike prior MBSE–DT or DT–MOM models, the DDTF establishes a closed adaptive loop connecting design intent, operational execution, and real-time feedback, aligned with INCOSE, ISA-95, and ISO 23247 standards. The framework advances academic discourse by introducing a cyber-physical epistemology for Operational Excellence and provides industry with a scalable blueprint for implementing digital continuity across the manufacturing lifecycle.

The findings confirm that the proposed framework directly supports conversion-cost optimization, 4Ms synchronization, and the elimination of non-value-added (NVA) activities—core pillars of Operational Excellence (Womack & Jones, 2003). The complementary Theoretical Framework for Operational Excellence (TFOE) extends Lean and Six Sigma principles into digital environments, embedding continuous improvement within the logic of cyber-physical systems.

Methodologically, this study demonstrates how systematic bibliographic synthesis can integrate diverse disciplines, consolidating fragmented knowledge into a coherent theoretical foundation. This approach ensures academic robustness while preserving industrial relevance. The integration of methodological evidence (Tables 1–7) and the proposed validation roadmap (Table 9) ensures that the DDTF is both theoretically grounded and empirically actionable.

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Ultimately, this research reframes digital transformation as a systemic redefinition of knowledge flow, adaptability, and decision-making, rather than a mere technological implementation. The Dynamic Digital Thread Framework provides a conceptual and practical foundation for realizing human-centric, resilient, and intelligent manufacturing ecosystems aligned with the vision of Industry 5.0. Future empirical studies should validate the DDTF as a reference architecture to guide the digital transformation of manufacturing enterprises across diverse industrial contexts.

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