

A systematic review of digital twins as decision support systems: a classification framework and identification of organisational constraints

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Abstract

Digital twins (DTs) are increasingly framed as decision support systems (DSSs), yet no framework has systematically examined how DT configuration shapes the decision support they provide. This study presents a systematic literature review of 299 studies from four databases, using Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) to examine how DT configuration influences decision support and value realisation. We develop a four-dimensional classification framework comprising abstraction level, DSS mechanism, decision level, and value type, and statistically test the relationships between these dimensions. The results show that DTs support decisions through four distinct mechanisms that differ in how information flows and how involved the decision maker remains. Model-driven DTs, which compute answers through embedded models, take on more of the reasoning themselves, whereas knowledge-driven DTs, which let users explore scenarios, keep decision makers actively involved. Whether a DT delivers value depends on organisational conditions as much as on its technical capability. Fully automated decisions are rare and occur mainly in model-driven DTs, suggesting that governance and accountability, rather than technology, limit automation. Model-driven DTs are also seldom used for long-term strategic decisions, as are DTs that represent only a single component rather than a wider system or enterprise. These patterns have been stable over time and do not appear to be driven by the uneven spread of studies across industries. Overall, the findings indicate that DT value depends on alignment with organisational decision contexts rather than technical sophistication alone. This paper highlights organisational and governance factors that cannot be captured by purely technical analyses.

Keywords: Digital Twins, Decision Support Systems, Organisational Decision Making

1. Introduction

The Digital Twin (DT) has evolved from a static "mirror image" of a physical object into a dynamic system defined by automated, bidirectional data exchange between a physical entity and its virtual counterpart [1], [2]. This bidirectionality rests on a premise that data drawn from a physical system becomes more valuable once it is processed in the virtual entity and returned as actionable feedback. As DTs scale from individual components to interconnected systems and enterprise-wide configurations [3], [4], they are positioned not merely as technical artefacts but as instruments that improve how an organisation decides and acts.

Yet the evidence for the value that DTs deliver is thin. A recent umbrella review of product DT research concludes that there is little evidence or understanding of how DTs actually create value, and argues that research and practice should concentrate on the elements of a DT that genuinely affect organisational outcomes rather than on technical sophistication for its own sake [5]. This shortcoming has a recognised cause: DT research has tended to advance through a "practice first, concept later" pattern that lacks a firm theoretical basis [6], and inappropriate choices about a DT's level of sophistication can produce strategic misalignment, inflated expectations, and cost without commensurate benefit [7]. The question of *value* has been left to engineering intuition rather than examined through any theory of how decisions are actually supported.

This is where understanding DTs as Decision Support Systems (DSSs) can bridge the gap. A DSS is a computer-based system that assists, rather than replaces, human decision makers by integrating data, models, and domain knowledge [8]. A DT functions as a DSS when it uses its representation of a physical system to inform the decisions an organisation must make about that system. Consequently, the central question shifts from what a DT is to which decisions it supports, and at what cost. Adopting this lens identifies three gaps that purely technical analyses cannot capture. First, it is unclear *how* DTs are implemented as DSSs. Second, it is unclear *what* business value DTs offer once implemented as a DSS, and under what conditions that value is realised. Third, and least examined, it is unclear what business value DTs *cannot* deliver as DSSs, regardless of their technical sophistication.

The third gap is the most consequential, because it runs against a prevailing assumption that "data is the new oil" [9]. As the unprecedented growth in the volume, velocity, and variety of data becomes available, the contemporary constraint on decision making is not a scarcity of data; more often it is excess [10], [11]. Power once lay in access to information; it now lies in the ability to filter, prioritise, and contextualise it - a long-standing challenge in bounded rationality theory [12]. Therefore, a DT should be 'fit for purpose'. Instead of maximising its fidelity and resolution, it should match the decision task [13].

Existing DT reviews do not address the challenge, because they treat the DT as a technical artefact rather than a DSS. **Conceptual reviews** clarify what DTs are and how they differ from related concepts such as simulation [14], the metaverse [6], or cyber-physical systems [15]. **Domain-specific reviews** catalogue applications within manufacturing [16], [17], healthcare [18], [19], and civil infrastructure [20]. **Technology-focused reviews** examine enabling technologies such as machine learning [21], the Internet of Things (IoT) [22], and visualisation for human-DT interaction [23]. A 2026 umbrella review of 79 DT systematic reviews identified the human and organisational dimension as a limiting factor in DT adoption, calling for human-in-the-loop DTs and usability-driven design [24]. The closest work to ours is a 2025 conference presentation by Inyang et al. [25]. They outlined a systematic review of DT-based DSSs for natural disaster management. As a presentation without an accompanying peer-reviewed publication, its methodology and findings are not available for replication. Their analysis catalogued data sources and data types rather than examining how a DT's configuration relates to the decision value it delivers. The systematic relationship between DT configuration and decision-support outcome therefore remains unestablished in the published literature.

This review addresses that absence by classifying DTs according to established decision-support frameworks, enabling systematic analysis of the relationship between DT configurations and decision support outcomes. The study is guided by three research questions (RQs):

RQ1: What decision-support mechanisms do DTs offer, and how do they differ in terms of information flow and the role of human-in-the-loop?

RQ2: How do DT configurations generate value, and what conditions constrain the realisation of this value?

RQ3: What systematic relationships exist between DT configurations and decision-support outcomes, and what do these patterns reveal about the organisational constraints on DT capabilities?

The remainder of this paper is organised as follows. Section 2 establishes the theoretical foundations, surveying DT classification frameworks and DSSs in organisational decision making. Section 3 describes the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guided methodology and presents a four-dimensional classification framework linking DT configuration to decision-support outcomes. Section 4 presents the findings across the three research questions. Section 5 synthesises these findings and discusses implications for research and practice. Section 6 sets out the limitations of the review, and Section 7 concludes with the principal contributions and future research directions.

2. Related Work

2.1 Classification Frameworks for Digital Twins

Existing frameworks for classifying DTs are typically based on one of the following four perspectives: data flow; scope; maturity; and integration. Each classification framework emerged from distinct technical or analytical motivations and offers useful insights into how DTs are configured.

Data flow-based classification frameworks distinguish DTs based on the direction and automation of data exchange between physical and virtual entities. Kritzinger et al. [2] formalised the distinction between Digital Models (no automated data exchange), Digital Shadows (automated one-way flow from physical to virtual), and DTs (automated bidirectional flow). Empirical evidence suggests that many systems labelled as DTs do not meet the bidirectional data flow criterion [2], [26].

Scope-based classification frameworks focus on the level of abstraction represented by a DT, ranging from DT Prototypes (created before the physical asset for design validation) and DT Instances (representing individual physical assets during operation), to DT Aggregates (combining multiple instances to identify patterns) [27]. From the perspective of physical system (de)composition, DTs can also be categorised as *component*, *asset*, *system* or *process* DTs, depending on the scope of the physical entity they represent [3]. More recently, enterprise-level DTs have emerged to integrate technical systems with business processes [28], [29]. Grieves' distinction [27] and subsequent architectural models [30] illustrate how multiple levels can be composed.

Maturity-based classifications position DTs along a capability scale from 0 to 5: 0 (standalone), 1 (descriptive), 2 (diagnostic), 3 (predictive), 4 (prescriptive), and 5 (autonomous) [31]. This staged view has recently been formalised at the standards level: the 2025 standard of the Institute of Electrical and Electronics Engineers (IEEE) for DT maturity assessment defines capability domains and subdomains alongside a structured assessment methodology for industry [32], and the 2025 maturity model of the International Organization for Standardization and International Electrotechnical Commission (ISO/IEC) takes a comparable generic approach, providing assessment indicators and guidance applicable across sectors [33]. Domain-specific extensions of this staged logic continue to appear: a 2025 construction-sector framework operationalises maturity across five layers - acquisition, data, modelling, analysis, and application - validated against a live industrial-park project [34]. Recent research also conceptualises extensions toward cognitive or adaptive capabilities [35].

Integration-based classification frameworks consider how DTs integrate multiple perspectives into unified schemes. Enders and Hoßbach [26] identify dimensions such as purpose (e.g. simulation, monitoring, control), connection type, completeness and creation timing. Van der Valk et al. [14] extend this by adding model fidelity, data synchronization, interface type and physical binding, capturing not only what a DT does but also how it interacts with and represents its physical counterpart. Boyes and Watson [36] proposed a functional component model that provides a systematic basis for characterising and comparing entities described as DTs. However, the framework remains oriented toward structural characterisation rather than the decision support functions DTs are intended to fulfil.

2.2 Classification Frameworks for Decision Support Systems in Organisations

To understand the role of DT in organisations, DTs must be viewed not only as technical artefacts but as DSSs. This section situates DSSs within the theoretical foundations of organisational decision making and introduces the frameworks used to analyse them.

Decision making is known as a process of identifying a problem, evaluating alternative courses of action and selecting an option under constraints. Herbert Simon emphasised that decisions are rarely made with complete information; rather, they are bounded by the rationality of the decision maker and the information available [12], [37]. A key distinction exists between individual and organisational decision making. Individual decisions typically involve a single actor who draws on limited information sources and is rarely required to justify the choice to others [38], whereas organisational decisions are collective and socio-technical [39], and are made under formal accountability, as decision makers must justify their choices within the organisation's authority structures. Organisational decisions involve multiple stakeholders with often conflicting objectives, distributed information systems and formal authority structures, spanning diverse workflows and temporal or spatial scales. Consequently, organisational decision making requires mechanisms that coordinate activities, integrate heterogeneous data and align functional units. DSSs are a well-established means of addressing this challenge.

DSSs are particularly valuable when organisational tasks are “semi-structured”, meaning that functional specifications cannot be fully pre-defined or the problem context is still evolving [40]. Modern DSSs support scenario analysis, forecasting and evidence-based evaluation, helping

organisations reduce uncertainty while enabling better-informed decisions. Beyond uncertainty reduction, DSSs can generate distinct forms of business value: *informational* value arises from improved availability and interpretability of data; *transformational* value occurs when decision processes themselves are reshaped; and *automational* value is realised when routine decisions are partially or fully automated [41], [42].

To classify how DSSs function, Power [43] developed a typology which distinguishes systems according to their dominant technological driver:

- **Data-driven DSSs** emphasise access to and manipulation of large internal or external data sets.
- **Model-driven DSSs** use computational models to simulate outcomes that inform decision making.
- **Knowledge-driven DSSs** incorporate domain expertise and problem-solving knowledge to provide tailored guidance.
- **Communication-driven DSSs** facilitate collaboration among multiple decision makers, often in group-based settings.

Alternative frameworks exist in the broader literature on decision making, including impact-driven models (e.g., McKinsey's ABCD model [44]), programmed vs non-programmed distinctions [45], or complexity-oriented approaches such as the Stacey Matrix [46]. While these frameworks provide insight into behavioural, political or cognitive dimensions of organisational decisions, they are less focused on the technological mechanisms through which decisions are supported.

Complementary perspectives come from management information systems research. Anthony's framework for management planning and control [47], extended in the "Framework for Management Information Systems" [8] and later popularised in broader management literature [48], distinguishes decisions along Strategic-Tactical-Operational (STO) dimensions. This framework situates decisions within time horizons, managerial authority and organisational scope, providing a structured vocabulary for locating decision-making activities.

2.3 Discussion

The classification frameworks reviewed in Sections 2.1 and 2.2 each provide valuable technical and conceptual clarity. However, a systematic examination reveals a persistent gap between how DTs are classified and the organisational decisions they are intended to support.

Within the DT literature, classification frameworks tend to foreground architectural and technical properties rather than decision support functions. Specifically:

- Data flow-based classifications, while technically precise, are decision-agnostic. Bidirectional data exchange enables control actions but does not, in itself, indicate which decisions the system supports.

- Scope-based frameworks describe what a DT represents but do not determine what decisions it informs, since the same component-level data might inform operational maintenance or long-term strategic planning depending on the DSS implementation.
- Maturity-based classifications, by positioning analytical sophistication on a linear capability scale of 0 to 5, imply that higher levels have higher capability. Yet this assumption warrants contextualisation: highly prescriptive systems may suit routine operational decisions, whereas strategic decisions often require curated descriptive insights that preserve human judgement.
- Integration-based frameworks, though comprehensive in their coverage of architectural dimensions, remain primarily structural: they characterise design patterns without specifying the organisational decisions the DT is intended to support.

Taken together, these classifications emphasise how DTs are configured rather than the organisational purposes they serve. They do not specify which organisational decisions are supported or what forms of value are realised - an omission that reflects the engineering-led origins of DT research, in which technical fidelity and data integration have taken precedence over organisational decision theory. This omission extends beyond classification frameworks: an umbrella review of product DT literature found little evidence and understanding of DT value, concluding that research and practice should focus on those elements of the DT that provide value to the organisation rather than pursuing technical sophistication [5].

The DSS literature offers frameworks better suited to bridging this gap. Power's typology [43] is particularly relevant for analysing DTs because it explicitly addresses the role of information systems in decision support, providing a vocabulary to distinguish the type of support provided and its functional impact on organisational processes. When combined with Anthony's Strategic-Tactical-Operational framework [47], it becomes possible to characterise DT configurations both in terms of the decisions they support and the mechanisms through which that support is delivered. The classification framework developed in Section 3 builds on this conceptual foundation. Without such a framework, the central question of whether DT configurations systematically produce specific decision-support outcomes could only be addressed narratively, through illustrative examples rather than testable evidence. The classification framework developed in Section 3 also allows these relationships to be tested statistically across the full corpus of papers included in this review (Section 4.4).

3. Methodology

This study adopts a systematic literature review guided by the PRISMA framework [49] to examine how DTs are used as DSSs in organisational contexts. The PRISMA framework provides a transparent and replicable approach for identifying, screening and synthesising relevant studies, thereby reducing selection bias and supporting reproducibility. This approach is supplemented by guidelines from Templier and Paré [50] to inform the search strategy, screening criteria and synthesis approach tailored to reviewing literature on information systems. Accordingly, this review is structured around the three research questions presented in Section 1, which guide the analysis of DTs as DSSs in organisational contexts.

3.1 Search Strategy and Record Identification

The search strategy was developed using the Population, Intervention, Comparison, Outcome, and Context (PICOC) framework, a structured approach for deriving search terms in systematic reviews [51] that has been widely adopted in information systems and software engineering reviews [52]. PICOC was selected over an unstructured term-generation process because it ties each search term to an explicit element of the review question, improving transparency and reducing the risk that relevant terminology is omitted. Table 1 maps each PICOC element to the search terms used.

For this review, the Population is DT; the Intervention is its use to support organisational decisions; the Outcome is the decision support provided or value generated; and the Context is the organisational decision-making setting. No Comparison element was specified, as systematic reviews of DT applications rarely contrast a DT-supported decision against a defined control condition; the element is therefore reported as not applicable, consistent with guidance that not every PICOC element need be populated when the review question does not warrant it [52].

The Intervention block warrants particular note. Decision support in the DT literature is frequently delivered without the explicit terms "decision support" or "decision making," through functionally equivalent activities. An earlier formulation of this search captured only "decision support" or "decision making," which risked excluding relevant work. However, indiscriminately broadening the block to generic analytical terms such as "optimisation," "planning," or "predictive" was found to be counterproductive: these terms denote computational methods rather than decision support, and their inclusion returned a corpus dominated by technically adjacent studies with no decision focus. The Intervention block was therefore restricted to terms that specifically denote a decision being supported - "decision support," "decision making," "scheduling," and "prescriptive" - each selected on the principle that the term names a decision activity rather than a computational one.

The Context element was handled in two stages. It was deliberately not encoded as a Boolean requirement in the database search string, because most DT decision-support studies do not use the word "organisation" in their title, abstract, or keywords even when situated in a clearly organisational setting; encoding it as a search term would conflate a topical judgement with a lexical one and bias the corpus towards managerially-framed work. Instead, the Context was operationalised at the screening stage through a set of organisational-entity terms - organisation, enterprise, company, and business - that denote a collective decision-making entity, as distinct from a single individual operator or a purely technical application scenario. Terms denoting an application scenario alone (for example, factory, hospital, or energy) were deliberately excluded from this set, as they indicate where a decision occurs but not whether it is organisational in nature.

Table 1. PICOC elements and corresponding search terms

PICOCelement	Concept	Search terms
Population	Digital twin	"digital twin"
Intervention	DT use to support decisions	"decision support" OR "decision making" OR scheduling OR prescriptive
Comparison	-	Not applicable
Outcome	Decision support / value	Captured via Intervention; assessed at screening

PICOCelement	Concept	Search terms
Context	Organisational setting	organisation OR enterprise OR company OR business (applied at screening, not in the search string)

Scopus, Web of Science, IEEE Xplore, and ScienceDirect were selected as bibliographic databases. Scopus and Web of Science provide broad interdisciplinary coverage across engineering, computer science, and management [53], while IEEE Xplore and ScienceDirect were included to strengthen coverage of the technical literature in which DT decision-support applications frequently appear, addressing the engineering orientation of the field.

Searches were conducted across the title, abstract, and keyword fields in all databases to ensure consistency, since this is the only field scope the databases share equivalently. The wildcard (*) was used where supported (Scopus, Web of Science, IEEE Xplore) to capture lexical variants; ScienceDirect, which does not support wildcards, used explicit plural forms. The canonical search string is presented in Table 2, adapted to each database's field syntax while preserving title-abstract-keyword scope. Database searches were conducted at the end of June 2026.

Table 2. Search queries by database

Database	Search Query
Scopus	TITLE-ABS-KEY("digital twin*") AND TITLE-ABS-KEY("decision support*" OR "decision making" OR scheduling OR prescriptive)
Web of Science	TS=("digital twin*") AND TS=("decision support*" OR "decision making" OR scheduling OR prescriptive)
IEEE Xplore	("digital twin*") AND ("decision support*" OR "decision making" OR scheduling OR prescriptive), scoped to Document Title, Abstract, Index Terms
ScienceDirect	("digital twin" OR "digital twins") AND ("decision support" OR "decision making" OR scheduling OR prescriptive), scoped to Title, abstract, keywords

The combined search returned 20,263 records (9,076 Scopus; 5,396 Web of Science; 3,997 IEEE Xplore; 1,794 ScienceDirect). All records were exported with full bibliographic metadata and processed using a Python script to support systematic and reproducible screening.

3.2 Screening and Selection

Screening proceeded in sequential stages: de-duplication, mechanical pre-screening, an organisational-context filter, removal of review articles, verification of full-text accessibility, and manual abstract screening (Section 3.3). Inclusion and exclusion criteria were defined a priori, assigned identifiers, and applied consistently throughout (Table 3). Records from the four databases were consolidated and de-duplicated using a Python script, matching first on normalised Digital Object Identifiers (DOIs) and then on normalised titles to capture studies indexed inconsistently across databases. Of 20,263 records identified, 8,239 DOI duplicates and 289 title duplicates were removed, yielding 11,735 unique records.

Three objective criteria were then applied mechanically. Records were excluded where the title did not contain the phrase "digital twin" (C3; -5,811), where the document was not a journal or conference paper (C2; -947), or where no DOI was present (C5; -194), leaving 4,783 records. Records with a missing document-type label or unparseable year were retained and resolved manually, so that no record was excluded on a metadata gap alone.

The organisational-context criterion (C4) was applied as an automated filter: a record was retained only if its title, abstract, or keywords contained an organisational-entity term (organisation, enterprise, company, or business), identifying decisions made by or for a collective entity. This reduced the corpus to 708 records. The filter operationalises organisational relevance by vocabulary and was confined to entity terms rather than application-scenario terms to preserve conceptual focus; it may exclude studies that frame organisational decisions in purely technical language, a trade-off noted as a limitation.

Review and survey articles missed by the article-type filter were then identified from their titles and abstracts and removed. As secondary studies, reviews synthesise primary research that is itself eligible for inclusion; retaining both would introduce the same underlying evidence into the corpus twice and bias the synthesis toward frequently-reviewed topics [52], [54]. This removed 52 records, leaving 656.

Finally, full-text accessibility (C5) was verified. Open-access availability was determined automatically via Unpaywall (268 records, 40.9%), and the remainder were checked manually against the authors' institutional subscriptions (a further 306 accessible). In total, 574 of 656 records (87.5%) were obtainable. The remaining 82 records were excluded under C5 (53 behind an unsubscribed paywall) and C1 (29 non-English). The resulting 574 records proceeded to manual abstract screening.

Table 3. Inclusion and exclusion criteria for literature screening

ID	Criterion	Inclusion	Exclusion
C1	Language	English	Non-English
C2	Article type	Journal articles, conference/proceedings papers	Book chapters, books, reviews, preprints, editorials, notes, letters
C3	Title relevance	"digital twin" present in title	"digital twin" absent from title
C4	Content focus	Addresses a DT for organisational decision-making or decision support operationalised by the presence of an organisational-entity term (organisation, enterprise, company, business) with empirical evidence or validated implementation	Peripheral DT reference; no organisational-entity term; no decision-support dimension; conceptual framework without empirical validation
C5	Accessibility	Full text available; DOI present	Full text unavailable; DOI missing
C6	Temporal	Published up to and including June 2026	Published after June 2026

3.3 Inclusion and Full-text Assessment

The 574 accessible records were first screened at the abstract level against the three research questions. A study was retained where its abstract indicated a DT applied to an organisational decision-making context with empirical evidence or a validated implementation. Abstracts that were ambiguous on any of these points were carried forward to full-text assessment rather than excluded, so that no study was rejected on the strength of its abstract alone. This stage excluded 99 records, most frequently as review or conceptual papers that had escaped earlier filtering, or as studies with no decision-support dimension. It left 475 records for full-text assessment.

Each of the 475 records was then read in full and coded against the classification framework. A further 176 records were excluded at this stage. The most common grounds were the absence of a validated implementation on close reading, and the lack of a genuine decision-support function despite a promising abstract. The full-text assessment yielded a final corpus of 299 studies.

3.4 Final Corpus

Following the complete screening and selection process, 299 studies met all inclusion criteria and formed the final corpus. Figure 1 presents the PRISMA flow diagram [55], detailing the record counts at each stage. The final corpus consists exclusively of peer-reviewed journal articles and conference papers reporting validated implementations or empirical evidence, ensuring the quality and relevance of the analysed literature.

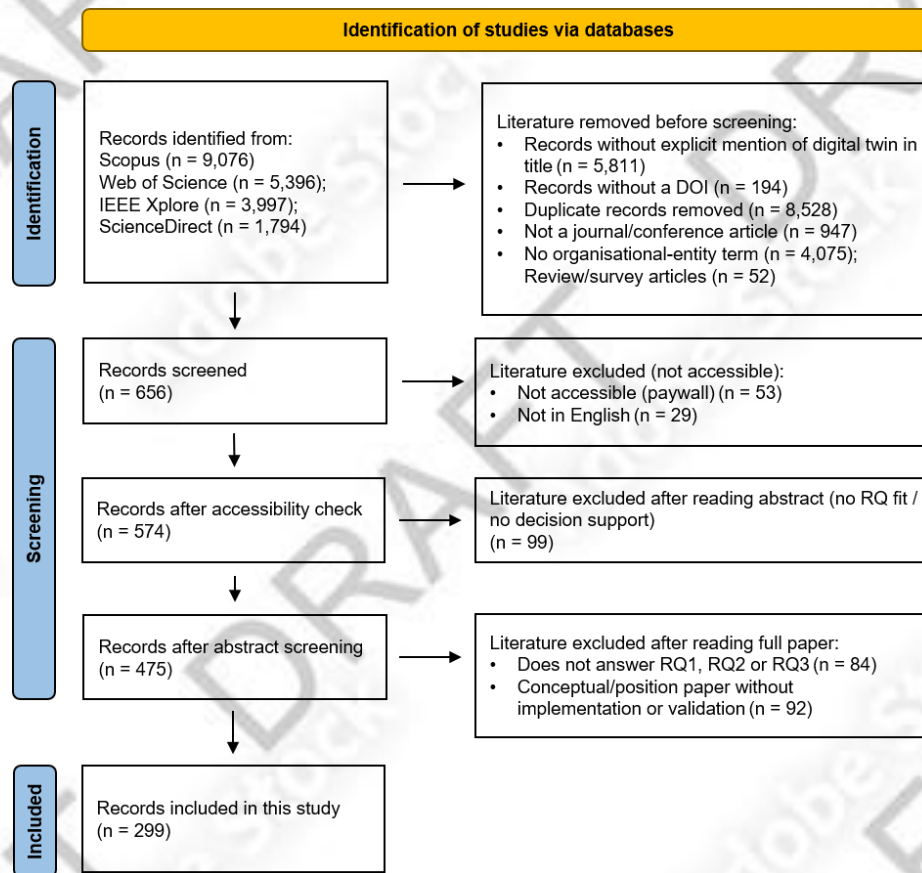


Figure 1. PRISMA 2020 flow diagram of study identification, screening, and inclusion, with record counts at each stage (n = 299 studies included).

3.5 Proposed Classification Framework

After analysis of the selected papers, a classification framework was created to understand the methodologies and trends used in the development of DTs as DSSs. The framework was

developed following the taxonomy design method proposed by Nickerson et al. [56], which provides a rigorous, iterative approach combining both conceptual (deductive) and empirical (inductive) reasoning. Although this method is framed as taxonomy development, the resulting artefact is referred to as a *classification framework* throughout this study - a taxonomy implies structural relationships between dimensions, whereas this study seeks only to identify empirical trends across groupings. Nickerson et al.'s [56] method is a well-adopted approach in information systems research and was further refined by Kundisch et al. [57], who emphasise the importance of clearly articulating the meta-characteristic, ending conditions and evaluation criteria.

The first step is to define a meta-characteristic - the overarching property from which all dimensions and characteristics must logically derive [56]. The meta-characteristic reflects the purpose and intended users of the classification. For this study, the meta-characteristic is defined as: *characteristics of DT-based DSSs that enable analysis of the correspondence between DT configurations and decision support outcomes*. This framing serves two user groups: researchers seeking to identify patterns and constraints in DT-DSS correspondence, and practitioners seeking guidance on aligning DT design choices with intended outcomes.

The meta-characteristic necessitates dimensions that capture both the configuration of DTs and the outcomes they produce. Four dimensions were selected through a conceptual-to-empirical approach, drawing on established theoretical frameworks identified in Section 2 (as summarised in Table 4):

- *Abstraction level*, derived from scope-based DT classifications (Section 2.1), captures the organisational scope of the DT, namely *component twins*, *system twins* and *enterprise twins* [3], [28]. This dimension enables analysis of whether scope of representation constrains decision-support capabilities.
- *DSS mechanism*, derived from Power's [43] DSS typology (Section 2.2), captures the functional approach through which decision support is delivered. This dimension enables analysis of how different mechanisms relate to different outcomes.
- *Decision level*, derived from Anthony's management framework as operationalised by Gorry and Scott Morton [8] and Carpenter et al. [48] (Section 2.2), captures which organisational decisions the DT supports. This dimension enables identification of boundary conditions on DT applicability.
- *Value type*, derived from Mooney et al.'s value classification [41] (Section 2.2), captures the form of business value generated. This dimension enables differentiation between the outcomes of different implementations.

Table 4. Dimensions of the proposed classification framework.

Role	Dimension	Core Question	Categories
DT Configuration	Abstraction Level	What organisational scope does the DT represent?	Component Twin System Twin Enterprise Twin
	DSS Mechanism	What functional mechanism delivers decision support?	Data-driven Model-driven Knowledge-driven

Role	Dimension	Core Question	Categories
			Communication-driven
Decision Support Outcomes	Decision Level	Which organisational decisions does the DT support?	Operational Decision Tactical Decision Strategic Decision
	Value Type	What type of business value does the DT generate?	Informational Value Automational Value Transformational Value

Each dimension was selected because it (i) derives logically from the meta-characteristic, (ii) is grounded in established theory, and (iii) enables analytical questions about the DT-DSS relationship that cannot be addressed by other dimensions. Following Nickerson et al. [56], the iterative development process concluded when the following objective ending conditions were satisfied: all dimensions are unique and not duplicated; all characteristics within each dimension are mutually exclusive; at least one study in the corpus maps to each characteristic; and no new dimensions or characteristics emerged in the final iteration. Collapsing these dimensions would obscure critical configuration variations and impose assumed relationships that this study seeks to empirically identify. Subjective ending conditions were also applied: the framework is concise (limited to dimensions necessary for the meta-characteristic), robust (withstands examination of diverse cases), comprehensive (accommodates all relevant objects), and explanatory (provides meaningful distinctions) [57].

3.6 Data Extraction and Synthesis

Each of the 299 studies in the final corpus was coded against the four classification-framework dimensions in Table 4 (abstraction level, DSS mechanism, decision level, value type), together with its application domain, publication year, and document type. Coding was conducted by the first author, with ambiguous cases resolved through discussion with the second author, consistent with the full-text assessment procedure described in Section 3.3.

Each study was assigned a single, primary category per dimension. Where a DT implementation addressed more than one decision level, mechanism, or value type in principle, the category coded was the one most substantively developed and evidenced in the study. This single-coding approach keeps every cell in the contingency tables analysed in Section 4.4 mutually exclusive, which the statistical tests applied in Section 4.4 require. In any case, most studies had one clearly dominant configuration and outcome during the full-text review, so the information lost to single-coding is limited. Instance counts across each dimension therefore sum to 299, the total size of the corpus, and this dataset is treated as fully categorical for the cross-dimensional analysis that follows in Section 4.4.

4. Findings

This section presents the findings of the systematic review. Section 4.1 provides an overview of the final corpus, characterising its composition by publication type, temporal distribution, and

application domain. Section 4.2 examines the decision-support mechanisms offered by DT configurations (RQ1). Section 4.3 analyses how DTs realise informational, automational, and transformational value (RQ2). Section 4.4 tests the cross-dimensional relationships between DT configurations and decision-support outcomes statistically (RQ3), reporting effect sizes and correcting for the multiple comparisons involved in testing every pair of framework dimensions.

4.1 Overview of the Corpus

As shown in Figure 2a, original research journal articles constitute the majority of the corpus (n=192, 64%; including one early-access article), with conference papers accounting for the remainder (n=107, 36%; including twelve records indexed by IEEE Xplore under a separate conference-proceedings label, harmonised here with conventional conference papers). No book chapters or stand-alone review articles remain in the final corpus, consistent with their removal at the article-type and review-removal stages of screening (Section 3.2).

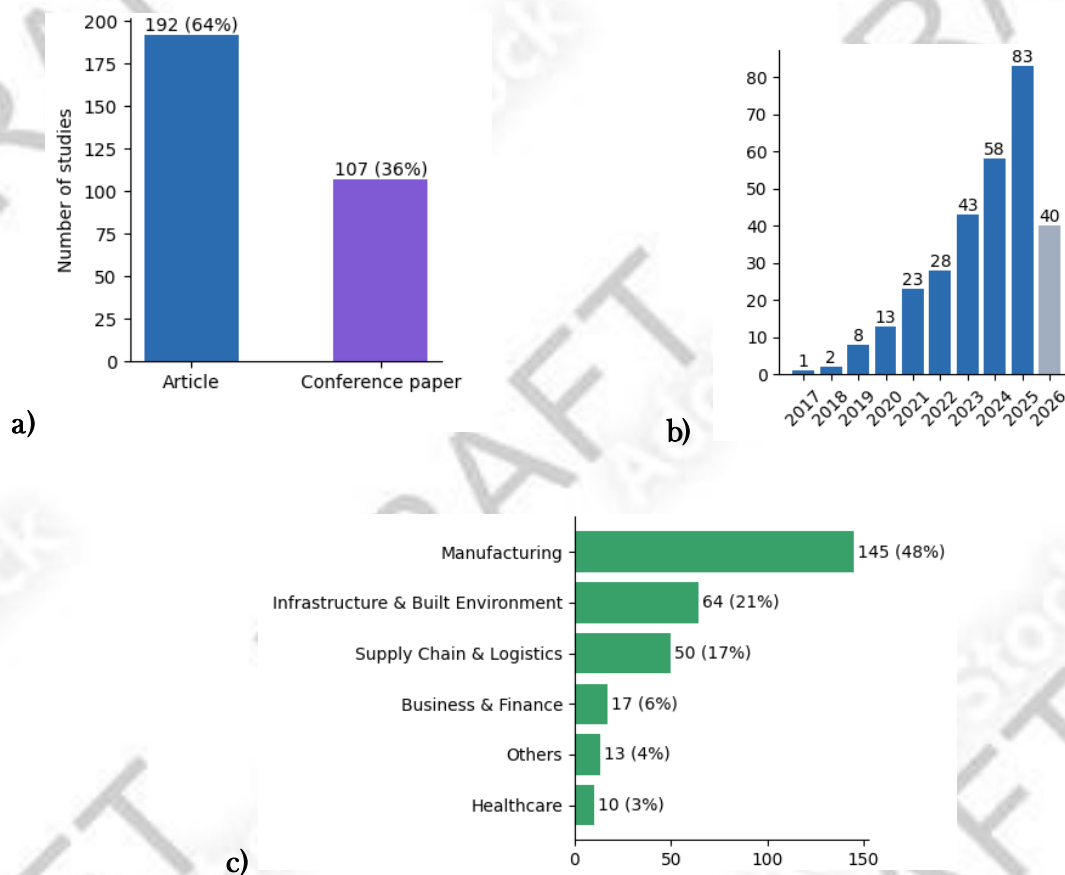


Figure 2. Overview of the final corpus: (a) publication type; (b) publications by year; (c) application domain (n=299).

The temporal distribution (Figure 2b) shows a corpus that grows steadily rather than emerging abruptly. Early publications are sparse: one study in 2017 and two in 2018, rising to eight in 2019

and thirteen in 2020. Growth accelerates from 2021 (n=23) through 2022 (n=28) and 2023 (n=43), before nearly doubling in 2024 (n=58) and reaching a peak of 83 studies in 2025. The apparent decline to 40 studies in 2026 is an artefact of the search cut-off date (end of June 2026, Section 3.1) rather than a genuine fall in research activity; 2026 should be read as a half-year count throughout this paper.

Figure 2c presents the distribution of studies across application domains. Manufacturing dominates the corpus (n=145, 48%), reflecting the historical origins of DT concepts in product life-cycle management and shop-floor operations. Infrastructure and the built environment form the second-largest domain (n=64, 21%), followed by supply chain and logistics (n=50, 17%). Business and finance (n=17, 6%), healthcare (n=10, 3%), and a residual ‘other’ category spanning energy and agriculture (n=13, 4%) account for the remainder. Energy-sector studies concerned with facility operation or maintenance, such as oil and gas or offshore installations, were coded as Infrastructure, reflecting the DT’s application function; the remaining energy and agriculture studies were too few to analyse as separate domains. This concentration in manufacturing and infrastructure is tested directly for confounding effects on the framework’s other dimensions in Section 4.4.4.

4.2 Digital Twin Implementations as Decision Support Systems

This section addresses RQ1 by examining how DTs are employed as DSSs. The focus is on how information and reasoning flow between the physical system, the DT, and the decision maker, rather than on how decisions are executed in the physical system. Applying the DSS mechanism dimension of the classification framework (Section 3.5) to the 299 studies in the corpus reveals four distinct mechanisms through which DTs support decision making: **data-driven, model-driven, knowledge-driven, and communication-driven**. These mechanisms are illustrated in Figure 3 and structure the discussion below. In Figure 3, directionality refers to the exchange of information between the DT and its user(s), which is distinct from the physical-digital data flow used in Section 2.1 to separate digital shadows from DTs. Interaction is unidirectional when the DT presents information or computed results to the decision maker (DT → Human), bidirectional when the decision maker also feeds assumptions or scenarios back into the DT and iterates on the results (DT ↔ Human), and multi-user bidirectional when several decision makers exchange information with one another through the DT (Human ↔ DT ↔ Human). Together, they show that the role of DT varies depending on where reasoning takes place and how decision makers interact with the system.

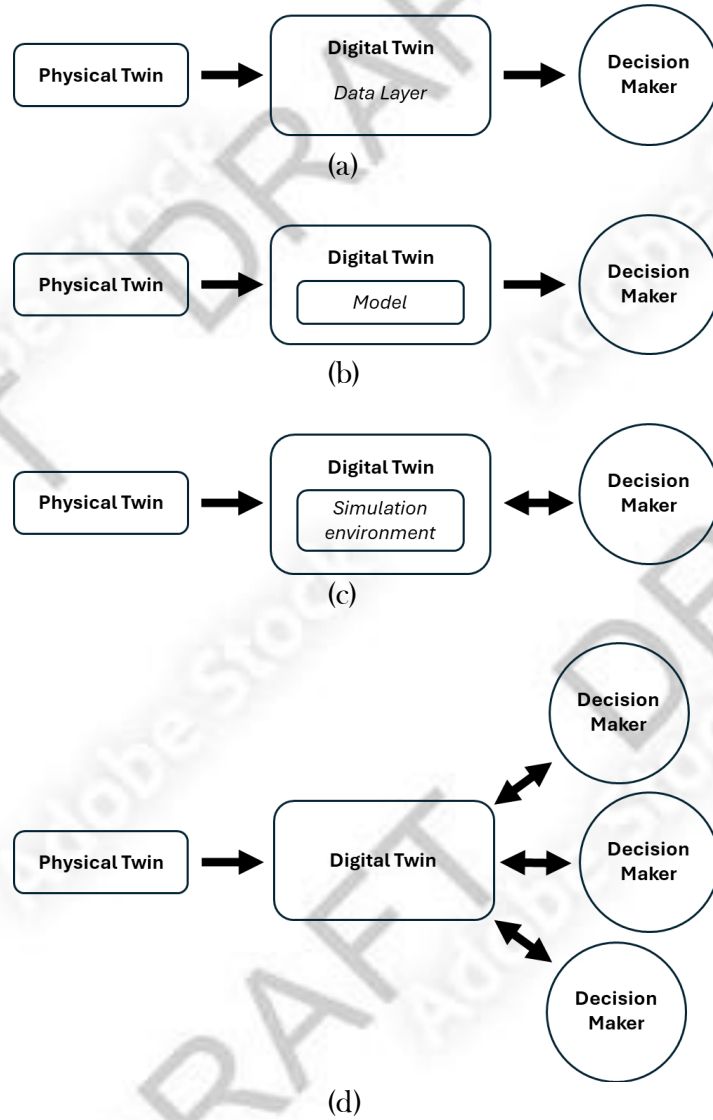


Figure 3. Information flow patterns in DT-based DSSs: (a) Data-driven DSS, (b) Model-driven DSS, (c) Knowledge-driven DSS and (d) Communication-driven DSS.

4.2.1. Data-Driven Decision Support Systems

Data-driven DT DSSs focus on retrieving and aggregating structured data to enhance situational awareness and evidence-based decision-making [58]. The DT assigns meaning to standalone information by utilizing context from the physical world to reduce ambiguity for specific stakeholders. For example, in road infrastructure management, these systems integrate data from multiple interacting subsystems into a systems-of-systems representation, providing a foundation for maintenance and life-cycle decision support [59]. Furthermore, the Virtual Bradford project provides a high-fidelity digital representation for local authority planning, while railway DTs manage multi-source data - including geological surveys, 3D models, and lidar - to support state description and problem diagnosis [60]. Similarly, tunnel operations and maintenance frameworks integrate spatio-temporal monitoring and inspection records to automate information extraction [61], and oilfield Visual Geographic Information Systems aggregate instrumentation and closed-

circuit television data into a single screen to provide comprehensive field situational awareness [62].

Within industrial manufacturing, data-driven DT DSSs provide a unified view of shop-floor operations by aggregating multi-source data to identify throughput bottlenecks via descriptive analytics and interactive dashboards. For instance, in pharmaceutical packaging, DTs report Overall Equipment Effectiveness metrics to help managers pinpoint suboptimal resource allocation [63]. In logistics, lightweight DTs for construction silos replace "gut feeling" with facts through continuous fill-level monitoring [42], while maritime frameworks track real-time carbon intensity by aggregating meteorological and Automatic Identification System data to ensure regulatory compliance [64]. In these environments, DTs are increasingly used for end-to-end visibility and status reporting across warehouses and transport fleets.

Finally, data-driven DT DSSs are expanding into healthcare and finance. Clinical patient DTs match present patient data against historical cohorts to provide evidence-based decision support for personalized treatment planning, such as immunotherapy [65]. In the public sector, DTs of built assets provide managers with a holistic visualisation alongside their funding sources by leveraging rule-based knowledge management to consolidate financial information [66]. Across all domains, data-driven DTs serve as an informative tool that guides human decision makers.

4.2.2. Model-Driven Decision Support Systems

Model-driven DT DSSs employ formal models to process inputs and autonomously generate outputs such as predictions, classifications or optimised solutions. In these systems, the reasoning logic is encapsulated within the model, and the human decision maker primarily receives computed results. The DT thus functions as an analytical tool, reducing cognitive effort by delegating a segment of reasoning to models. The literature identifies four main categories of models used within these systems.

Physics-based (mechanistic) models represent the internal behaviour of systems using first-principles equations or explicitly defined scientific hypotheses. These models are used for predictive maintenance, such as simulating the mechanical interactions and degradation curves of industrial robots [67].

Data-driven (empirical) models rely on historical data and machine learning to infer relationships that are difficult to model explicitly. Examples include using Long Short-Term Memory networks to diagnose internal leakage in aircraft electro-hydrostatic actuators by monitoring signal flow [68]. Additionally, predictive machine learning models are embedded within discrete-event simulations to forecast manufacturing system variables in real time and support dynamic decision-making during supply-chain disruptions [69].

Optimisation or rule-based models use predefined rules or mathematical approaches to compute optimal solutions under given constraints. A representative example is a DT for elective surgery scheduling that integrates patient-specific models with a reinforcement-learning optimiser to generate real-time prioritisation scores, aiming to reduce patient waiting times [70]. Similarly, rule-based systems are used to evaluate equipment health by weighting various descriptive indicators through expert-defined logic [71].

Finally, **hybrid models** combine data-driven and complementary approaches to address data scarcity or improve explainability. A common strategy involves using physics-based indicators as pre-processing for machine learning algorithms, as seen in infrastructure management for anomaly detection on reinforced concrete bridges [72]. These hybrid approaches are particularly effective in complex systems where purely data-driven methods may appear as "black boxes" lacking the physical transparency required by engineers.

4.2.3. Knowledge-Driven Decision Support Systems

Knowledge-driven DT DSSs differ from model-driven counterparts not by the absence of models, but by the location of reasoning agency, which resides in the interactive relationship between the human and the DT. These systems provide interactive, simulation-based environments where decision makers can explore diverse scenarios, test hypotheses and conduct rigorous what-if analyses. Rather than simply receiving a single computed answer, the human remains *in the loop*, actively including domain knowledge and steering the exploration while insights emerge through an iterative process of discovery.

In smart city planning, the Snap4City Smart City DT framework for Florence allows urban planners to perform what-if analyses by simulating traffic restriction zones and observing resulting trajectory changes and routing impacts in real time [73]. This interactive environment supports an experiential understanding of policy impacts, allowing designers to assess how changes in the existing landscape affect city-wide parameters like pollutant propagation and traffic flow density. In manufacturing, a knowledge-driven DT for a pharmaceutical plant enables managers to navigate complex production dynamics by simulating different resource allocations on packaging lines to identify bottlenecks and optimise machine utilization [63]. This allows for the risk-free testing of operational strategies and new technologies without disrupting live day-to-day operations.

Knowledge-driven mechanisms are also evident in business and logistics contexts. An Enterprise DT allows managers to run risk-free business experimentations to understand customer behavioural dispositions toward new product launches, such as unlimited data plans during the COVID-19 pandemic [29]. Decision makers iteratively test various product configurations and price points within the DT to evaluate efficacy and associated risks, arriving at an evidence-backed intervention strategy. Furthermore, supply chain DTs enable planners to analyse coherent scenarios for production and distribution activities, ensuring that solutions are aligned with real-world practices and sustainability goals without disrupting live operations [74]. Across these examples, insight generation depends on the human-in-the-loop and a continuous, iterative process of interaction with the DT.

4.2.4 Communication-Driven Decision Support Systems

Communication-driven DT DSSs emphasize collaboration, information sharing, and collective understanding among multiple stakeholders, both within and across organisational boundaries. They support group decision making by facilitating coordination, negotiation and consensus building, with DTs functioning as integration platforms that provide situational awareness. Interaction patterns are often multi-user and bidirectional, involving human-DT-human exchanges that leverage a continuously updated knowledge base to guide decisions.

In aviation equipment maintenance, DTs are used to replicate frontline maintenance support operations, generating shared real-time data to support decision making across the organisation [75]. In the context of Smart Grids, the concept of DT *communities* facilitates inter-organisational communication by allowing homologous organisations to share simulation results and predictions, such as electricity generation capacity or imminent surges in consumption [76]. These communities foster a collective intelligence that enhances situational awareness and infrastructure resilience.

Communication-driven mechanisms are also observed in social manufacturing and supply chain contexts. Blockchain-enabled DT platforms support trusted information exchange among production, distribution and warehousing actors, ensuring real-time visibility, traceability and synchronization of the entire process [77]. In urban governance and architecture, communication-driven DTs like Virtual Bradford support participatory planning by providing city-scale models that allow citizens and planners to engage with development scenarios and inform decisions regarding regeneration and infrastructure [60]. Similarly, in urban planning and governance, DTs are positioned as operative configurations within City Information Modelling, integrating heterogeneous actors and long-term uncertainty to facilitate multi-stakeholder decision-making [78].

Table 5 consolidates these four mechanisms, summarising the differences in DT role, interaction pattern, output type, and interaction directionality as discussed above.

Table 5. Summary of distinguishing characteristics of DT-based DSSs.

Dimension	Data-driven	Model-driven	Knowledge-driven	Communications-driven
DT Role	Information Gateway	Analytical Tool	Exploration Environment	Collaboration Platform
Interaction Pattern	Query (U) → Retrieve (DT) → Display (DT)	Input (U) → Compute (DT) → Recommend (DT)	Hypothesise (U) → Simulate (DT) → Learn (U) → Iterate (U)	Share (Us) → Discuss (Us) → Negotiate (Us) → Align (Us)
Output Type	Reports, KPIs, Alerts	Predictions, Optimal Solutions	Insights, Understanding, Testbed	Consensus, Coordinated Actions
Interaction Directionality	Unidirectional (DT → Human)	Unidirectional (DT → Human)	Bidirectional (DT ↔ Human)	Multi-user bidirectional (Human ↔ DT ↔ Human)

Note: U = single user (decision maker); Us = multiple users; DT = digital twin; KPI = key performance indicator.

4.3 Value Realisation in Digital Twin Implementations

This section addresses RQ2 by analysing how DTs realise organisational value. DT DSSs generate value in line with Mooney [41], which distinguishes informational, automational, and transformational value.

4.3.1. Informational value through reduced uncertainty

Informational value emerges when DTs provide better information that reduces uncertainty in outcomes. To achieve this, decision makers require accurate, timely and comprehensive information from the DT to transform data into actionable insights. For example, in highway asset management, DTs facilitate proactive maintenance by integrating inspection and structural-condition data into scheduled maintenance, repair, and rehabilitation planning [79]. In tunnel operations, this manifests through fault cause analysis of jet fans, where real-time monitoring and semantic reasoning allow for efficient diagnosis and maintenance planning [61].

Apart from enhancing the visibility of individual assets, revealing process interdependencies enables improved scheduling and resource allocation. For example, a DT framework can detect, diagnose and improve throughput bottlenecks in complex systems, providing "what-if" scenarios in real factory settings. In supply chains, DTs enhanced visibility and adaptability, helping organisations cope with disruptions and optimise inventory levels in response to COVID-19 [80]. Moreover, the integration of operational data with market information enables more informed strategic choices about capital investment and supply chain configuration. For instance, an Egyptian gas company utilized a DT integrated with multi-criteria decision making to assess sustainability risks and select the best suppliers, reducing overall supply risks [81].

The delivery of informational value depends on maintaining accurate state representation between the physical twin and DT. Consequently, DTs must capture not only system responses from sensors but also actions by decision makers. The technical challenge is distinguishing between consequences caused by deliberate human actions and system responses from environmental conditions or stochastic variation. When decision makers adjust equipment parameters, change process setpoints or redirect resources without these actions being recorded, the DT attributes all subsequent effects to natural system variation. Consequently, future predictions become inaccurate, and the operational picture becomes incomplete or inconsistent with expectations. In construction, for example, the virtual-to-physical connection is often not automated, making the logging of human involvement crucial for the DT to function as a reliable DSS [82].

This degradation is insidious - as operators make undocumented adjustments and managers modify procedures, the DT's representation diverges from reality and informational value declines. Sustained informational value requires a commitment to action logging as rigorous as sensor monitoring. In a study of tracking hydraulic drives, researchers developed a data logging layer specifically to record configuration parameter changes and system user actions, ensuring the DT reflects actual performance changes caused by human intervention [83]. Most implementations focus resources on sensor networks and underinvest in capturing human actions, a pattern observed consistently while coding the corpus.

4.3.2. Automational value through reduced human effort

Unlike informational value which improves human decisions, automational value comes from removing humans from certain decision loops. DTs generate this value by replacing manual activities with automated processes, such as continuous monitoring replacing physical inspections. In construction logistics, sensors are used to track silo fill levels to trigger pre-emptive replenishment, thereby avoiding manual ad-hoc material requests and work interruptions [42]. In the agri-food sector, DTs automate the analysis of time-series data to forecast incoming donations

and charity demand, replacing traditional manual communication methods. It enabled the supervision of perishable inventory across complex supply chain networks [84].

A key benefit of automating the coordination of interdependent processes is faster response in dynamic conditions. In intelligent shop floors, DTs automatically match manufacturing resources with tasks according to the real-time status of equipment, discovering and dealing with anomalies without human intervention [85]. This is exemplified by smart workpieces capable of interacting with their environment and making proactive decisions regarding their own processing route, which eliminates the need for extensive manual coordination [86]. Furthermore, automated supply chain coordination reduces coordination costs across organisational networks; for instance, in social manufacturing, blockchain-enabled DTs use smart contracts to automate inter-organisation communication and the selection of logistics units during dynamic interruptions [87].

However, automational value can only be realised when three conditions are met: (i) sufficient data reliability and completeness, (ii) sufficient decision autonomy, such that human oversight is not required, and (iii) economically acceptable error risks.

First, the DT must have sufficiently reliable and complete data. One study in the corpus, examining a logistics DT for a nationwide distribution network, distinguishes three forms of incomplete visibility [88]. A breakpoint occurs where data cannot be digitalised reliably or is missing altogether, such as when a vehicle is obscured from a sensor or a device fails silently. A black box occurs when a process is digitalised at its beginning and end but not during the intervening activities, as in manual processes where only the outcome is recorded. A gray box occurs when data is temporarily unavailable but subsequently restored, such as when a tracked asset briefly leaves sensor range. These distinctions illustrate different ways in which insufficient information can constrain autonomous value. Importantly, this limitation is independent of the downstream analytical model.

Second, the decision must be sufficiently autonomous to be executed without human oversight. Many decisions that are technically automatable nevertheless require human approval for safety, quality, or regulatory reasons. In such cases, the DT can reduce analysis effort through decision support but cannot eliminate the decision-making step itself. Realised automational value is therefore the reduction in analysis effort, rather than the eliminated decision-making effort assumed by theoretical calculations. For instance, in delegated autonomy models such as those used in cognitive household DTs, software agents are authorised to execute energy-use decisions only within parameters set by the owner, balancing individual preferences with community sustainability goals [89].

Third, the risks of automation must be economically acceptable. Decisions with localised impacts and rapid reversibility can tolerate higher error rates because correction costs are low, whereas decisions with systemic impacts and difficult reversibility require much lower error rates. In distributed manufacturing, for example, an autonomous system might reject a rush order if the DT calculates that accepting it would compromise the delivery dates of existing orders, because the systemic cost of a delivery failure exceeds the value of the new order [85], [87]. Similarly, in aerospace, DTs used for automated structural health monitoring must employ high-fidelity probabilistic models to ensure that the risk of an erroneous “safe” diagnosis remains economically and regulatorily acceptable relative to manual inspection costs [90].

Together, these constraints show why automational value from DTs cannot be inferred from theoretical labour savings alone. It is only feasible where sufficient information is available, human intervention is unnecessary, and the residual risk of error is acceptable. Otherwise, the DT's value lies primarily in supporting rather than replacing human decision making.

4.3.3. Transformational value by enabling new capabilities

Transformational value is presented when DTs enable business capabilities or organisational structures that were previously impossible [63]. For instance, manufacturers can shift from selling products to selling outcomes, such as equipment uptime rather than the equipment itself. DTs provide the asset visibility needed to manage risk through frameworks like Product-Service Systems [77]. In terms of operations, organisations can adjust toward optimal conditions in real-time while maintaining quality. This is demonstrated in dynamic labour planning and capacity management models that adapt to unexpected fluctuations [91]. Furthermore, supply chain relationships can transform from vendor-to-vendor transactions to integrated, multi-tier ecosystems with shared data visibility. Ford Motor Company's supply chain DT programme, spanning intracompany, Tier-1, and deep-tier network layers, demonstrated resilience at scale that fragmented approaches cannot achieve [92].

Transformational value has a critical constraint often overlooked in DT literature. Automational value depends on the DT's ability to close the loop between virtual and physical space, whereas transformational value often depends on changing the system in which that loop operates - something the DT cannot do by itself. Based on Kritzinger et al.'s definition [2], bidirectional information flow enables a DT to execute decisions within an existing system architecture, such as adjusting parameters, triggering actions, or coordinating established processes. Transformational value, however, requires changes to the architecture itself, which typically involve human, organisational, or physical intervention [93], [94].

This distinction is important because literature often frames transformation as the “execution of decisions via the DT,” implying that transformational value follows automatically from deployment. For example, a DT could enable a hospital to manage surgical waiting lists through new, dynamic outcome-based service models [95]. However, realising such a model requires changes beyond the DT, including redesigned contracts, organisational structures, pricing models, and physical infrastructure such as IoT sensors and communication interfaces [96]. The DT therefore enables and supports transformation rather than executing it.

This has direct implications for business cases. Transformational value is often the largest expected benefit, particularly in complex implementations requiring substantial investment [73]. However, treating it as an automatic consequence of DT deployment can underestimate implementation costs and overstate the speed of value realisation [63]. Distinguishing between DT-executed automation and DT-enabled transformation is therefore essential for realistic value assessment and implementation planning.

4.4 Cross-Dimensional Patterns

This section addresses RQ3 by testing the relationships between DT configurations and decision support outcomes, rather than only describing. Five dimensions were coded across the corpus: abstraction level, DSS mechanism, decision level, value type, and application domain (industry). Taken pairwise, these five dimensions yield ten distinct relationships, each tested for statistical association, effect size, and robustness to confounding and to sampling variability. This moves the analysis from identifying which configuration-outcome combinations are common or rare in raw counts, to establishing which of those patterns are statistically distinguishable from what would be produced by chance.

4.4.1 Statistical approach

Results in this section are reported as Cramér's V (the effect size, on a 0–1 scale, with its 95% confidence interval in brackets) and p_{Holm} (the significance level after correcting for multiple comparisons, defined below). The full test statistic behind each result, namely χ^2 , degrees of freedom, and the uncorrected p -value, is reported once, in Table 6, rather than repeated in every sentence.

Association between each pair of categorical dimensions was tested using Pearson's chi-square test of independence, with effect size reported as Cramér's V , bias-corrected for the inflation that chi-square-based effect sizes exhibit in small or unevenly distributed tables [97]. A bootstrap 95% confidence interval was computed for each V estimate by resampling studies with replacement (2,000 resamples), so each effect size is reported with its own uncertainty band rather than as an unqualified point estimate. Where more than 20% of a table's cells had an expected count below five, a threshold below which the chi-square approximation becomes unreliable, this is reported explicitly alongside the result.

Because ten pairwise tests were conducted across the five framework dimensions, treating each at the conventional $\alpha = 0.05$ threshold would inflate the family-wise false-positive rate to approximately 40%. All ten p -values were therefore corrected using the Holm-Bonferroni step-down procedure [98], which controls the family-wise error rate at 0.05 while retaining more power than a flat Bonferroni correction. Only associations that remain significant after this correction are reported below as robust findings.

For each significant pairwise association, standardized (adjusted) residuals were computed for every cell of the corresponding contingency table (configuration–outcome pairs shown in Figure 4). An adjusted residual expresses how many standard deviations a cell's observed count departs from the count independence would predict, after accounting for the row and column totals. This is the statistic that distinguishes a configuration-outcome combination that is rare because of sampling variability from one that is rare because the combination is structurally disfavoured: $|z| > 1.96$ corresponds to $p < 0.05$ and $|z| > 2.58$ to $p < 0.01$ for that specific cell.

Table 6. Pairwise associations among the five framework dimensions, ranked by effect size.
*** indicates >20% of table cells with expected count < 5; to be treated as indicative.**

Pair	chi2(df)	N	p (raw)	V [95% CI]	p (Holm)	% cells < 5 exp.	Sig. (corrected)
Value type x DSS mechanism	204.29 (6)	299	<0.001	0.58 [0.53,0.63]	<0.001	0%	Yes
Decision level x DSS mechanism	150.05 (6)	299	<0.001	0.49 [0.41,0.57]	<0.001	0%	Yes
Decision level x Value type	116.81 (4)	299	<0.001	0.44 [0.38,0.49]	<0.001	0%	Yes
Industry x Abstraction level	92.88 (10)	299	<0.001	0.37 [0.30,0.48]	<0.001	33%	Yes*
DSS mechanism x Abstraction level	42.70 (6)	299	<0.001	0.25 [0.16,0.36]	<0.001	17%	Yes
Value type x Abstraction level	30.28 (4)	299	<0.001	0.21 [0.14,0.30]	<0.001	0%	Yes
Industry x Decision level	29.84 (10)	299	0.001	0.18 [0.13,0.30]	0.003	33%	Yes*
Industry x DSS mechanism	40.18 (15)	299	<0.001	0.17 [0.13,0.28]	0.002	38%	Yes*
Industry x Value type	25.26 (10)	299	0.005	0.16 [0.10,0.29]	0.010	33%	Yes*
Decision level x Abstraction level	14.33 (4)	299	0.006	0.13 [0.07,0.23]	0.010	0%	Yes

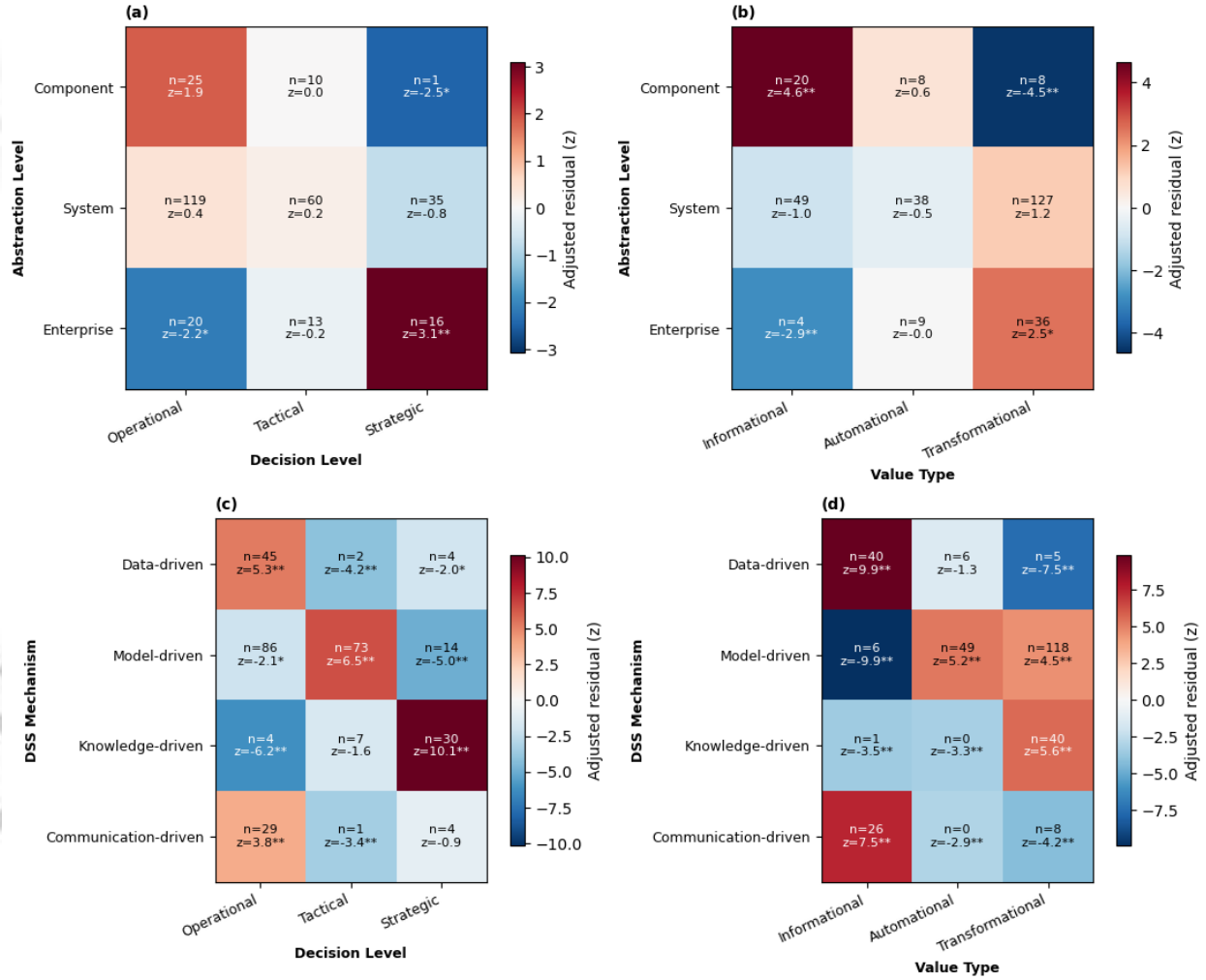


Figure 4. Standardized residuals for DT configuration and decision-support outcomes (n=299): (a) abstraction level and decision level; (b) abstraction level and value type; (c) DSS mechanism and decision level; (d) DSS mechanism and value type.
 * $|z| > 1.96$ ($p < 0.05$); ** $|z| > 2.58$ ($p < 0.01$), relative to independence.

4.4.2 DT Configuration and Decision Level

Abstraction level and decision level are significantly associated ($V = 0.13$ [0.07, 0.23], $p_{\text{Holm}} = 0.010$; Table 6). Figure 4a shows where the association concentrates: component twins are significantly under-represented among strategic decisions ($n=1$ of 36 component-twin studies; $z = -2.5$, $p < 0.05$), while enterprise twins are significantly over-represented there ($n=16$ of 49; $z = 3.1$, $p < 0.01$) and under-represented among operational decisions ($z = -2.2$, $p < 0.05$). System twins, the modal abstraction level, show no significant associations in any cell.

One study in the corpus illustrates that component twins can inform strategic decisions. However, their near absence is a statistically significant feature of the corpus. This reflects a fundamental limitation of isolated information: while component DTs enhance local situational awareness, they lack the relational and comparative context required for higher-order reasoning. Prior work on the value of information, notably Moody and Walsh's laws of information [99], holds that information

becomes more valuable when combined with other information: data becomes decision-relevant only when contextualized spatially, temporally or relationally - either against historical states or across interacting assets.

On the other hand, DSS mechanism and decision level show the strongest configuration-outcome association in the framework ($V = 0.49$ [0.41, 0.57], $p_{\text{Holm}} < 0.001$; Table 6). Figure 4c shows a clear division. Knowledge-driven mechanisms are strongly concentrated in strategic decisions ($n=30$ of 41; $z = 10.1$, $p < .01$) and significantly avoid operational ones ($z = -6.2$, $p < .01$). Model-driven mechanisms show the reverse pattern at the strategic end: despite being the most common mechanism overall, they are significantly under-represented among strategic decisions ($n=14$ of 173; $z = -5.0$, $p < .01$) and concentrated instead in tactical decisions ($n=73$; $z = 6.5$, $p < .01$). They are also under-represented among operational decisions relative to the corpus-wide base rate: 49.7% of model-driven studies are operational, against 54.8% corpus-wide ($z = -2.1$, $p < .05$). Data-driven and communication-driven mechanisms are both significantly concentrated in operational decisions ($z = 5.3$ and $z = 3.8$ respectively, both $p < .01$).

This statistically confirms the qualitative distinction drawn in Section 4.2: model-driven DSSs, which delegate reasoning to the model itself, are systematically tactical and operational tools, while knowledge-driven DSSs, which keep the human in the loop, are systematically a strategic tool. This pattern aligns with theories of bounded rationality, in which formal models encode predefined assumptions about system structure and causality to remain computationally tractable. While assumptions enable optimisation within well-specified problem spaces, they constrain strategic reasoning, where the central challenge lies not in optimising given constraints but in redefining or selecting those constraints themselves.

4.4.3 DT Configuration and Value Type

Value type and DSS mechanism show the strongest association of any pair in the framework ($V = 0.58$ [0.53, 0.63], $p_{\text{Holm}} < 0.001$; Table 6). Figure 4d shows that automational value is the only value type with a single, clearly dominant mechanism: it is significantly over-represented under model-driven mechanisms ($n=49$; $z = 5.2$, $p < 0.01$) and significantly absent under knowledge-driven ($n=0$; $z = -3.3$, $p < 0.01$) and communication-driven mechanisms ($n=0$; $z = -2.9$, $p < 0.01$). This is consistent with the account in Section 4.3.2: automational value requires a mechanism capable of executing a decision without a human in the interpretive loop, which model-driven systems are structurally suited to and knowledge- and communication-driven systems structurally are not.

Besides that, value type is also significantly associated with abstraction level ($V = 0.21$ [0.14, 0.30], $p_{\text{Holm}} < 0.001$; Table 6). Figure 4b shows component twins significantly over-represented for informational value ($n=20$; $z = 4.6$, $p < 0.01$) and significantly under-represented for transformational value ($n=8$; $z = -4.5$, $p < 0.01$), with the reverse pattern holding for enterprise twins. Notably, automational value shows no significant residual at all abstraction levels of component, system, and enterprise twins. If automational value were primarily constrained by a DT's technical scope, it should concentrate at a particular abstraction level; instead, its scarcity is uniform. This notion is consistent with the organisational-governance explanation, developed in Section 4.3.2, rather than a technical constraint.

4.4.4 Industry and Temporal Robustness

Because the corpus is unevenly distributed across industries, an association between two framework dimensions could in principle reflect the industries in which configurations happen to be common, rather than a property of the configuration itself. This was tested directly for the abstraction-level constraint reported in Section 4.4.2, using a Cochran-Mantel-Haenszel (CMH) test [100], which asks whether component-scope DTs remain under-represented among strategic decisions once industry is held constant. All six industry categories present in the corpus were used as strata (stratum sizes ranging from $n=10$ for healthcare to $n=145$ for manufacturing; none fell below the minimum of five studies needed to inform the pooled estimate). The pooled Mantel-Haenszel odds ratio was 0.18, in the same direction as the unstratified result, with a CMH statistic of 3.57 ($p = 0.059$). The association therefore retains its direction and a large effect size once industry is held constant, although it falls just short of conventional significance. With only six strata available, this test has limited statistical power, and the finding is reported with that caveat rather than as a fully confounder-adjusted result.

The extended period of publication (2017 – 2026) also makes it possible to test whether the mix of configurations and outcomes identified above is a stable feature of the field or a transitional stage. Publication years were grouped into three bands (2017–2020, $n=24$; 2021–2023, $n=94$; 2024–2026, $n=181$) and tested against DSS mechanism and value type. Neither test reached significance (DSS mechanism: $\chi^2(6, N=299) = 5.54, p = 0.48$; value type: $\chi^2(4, N=299) = 8.66, p = 0.07$), and Cramér's V was close to zero in both cases ($V = 0$ and $V = 0.09$ respectively). The mix of mechanisms and value types identified in this review has therefore remained stable across the period of most rapid growth in DT-DSS research, rather than shifting as the field matures. This suggests that the patterns reported above reflect a stable feature of how DTs function as DSSs rather than an early stage of a field still finding its configuration.

Table 6 reports all ten pairwise associations among the five framework dimensions, ranked by effect size, with Holm-Bonferroni-corrected p -values. All ten relationships remain statistically significant after correction, though effect sizes range considerably, from $V = 0.58$ (value type and DSS mechanism) to $V = 0.13$ (decision level and abstraction level). Three pairs involving industry (marked * in Table 6) had more than 20% of contingency-table cells with an expected count below five; these associations are real at the corpus level but should be treated as provisional pending a larger or more evenly distributed corpus, rather than as precise effect-size estimates.

5. Discussion

This review reveals that DT development reflects an ongoing organisational negotiation between technical capability and the realities of decision-making practice. The four subsections below apply three distinct lenses to the findings established in Section 4: sociotechnical design (Sections 5.1 and 5.2), barriers to automation (Section 5.3), and the role of artificial intelligence (Section 5.4).

5.1 Socio-technical Design in Industry 4.0

The founding Industrie 4.0 report organised its recommendations around five working groups, one of which - Human Beings and Work - addressed workforce qualification, new forms of work organisation, and the allocation of responsibility within increasingly automated production networks [101]. This emphasis reflects a sociotechnical perspective, which holds that organisational performance emerges from the joint optimisation of technical and social subsystems. However,

much of the DT literature that subsequently emerged from the Industry 4.0 discourse has placed substantially greater emphasis on the technical subsystem. Most prominently, Kritzinger et al. [2] define a ‘true’ DT through automated, bidirectional data exchange between physical and digital entities, positioning unidirectional ‘digital shadows’ as intermediate or less mature configurations. In doing so, this framing gives comparatively little attention to the organisational and governance conditions under which human involvement may remain necessary or desirable.

The findings of this review highlight the consequences of this technical emphasis. Automational value was scarce even among DTs with bidirectional technical architectures, while unidirectional configurations were frequently used in contexts where human oversight remained appropriate. This suggests that unidirectional data flows should not necessarily be interpreted as technologically immature stages on a path towards full automation. Rather, they may represent deliberate architectural choices. In this respect, the findings are more consistent with the original sociotechnical framing of Industry 4.0 than with a purely technology-driven maturity model. The subsequent emphasis on human-centricity in the European Commission’s Industry 5.0 initiative similarly reflects recognition that industrial digitalisation cannot be reduced to technological capability or efficiency alone [102].

This perspective has implications for how DT architectures are classified. The distinction between digital shadows and DTs may be more usefully understood as a distinction between alternative configurations of data flow and decision authority, rather than as a linear hierarchy of technological maturity. Consequently, the current lack of definitional consensus surrounding DTs may be viewed as a generative asset rather than a limitation, as it allows DTs to serve as flexible integration mechanisms for multidisciplinary data across diverse sectors.

5.2 Reference Architectures and the Absence of Decision Authority

This same technical emphasis characterises the formal reference architectures that operationalise DTs. The Reference Architectural Model Industrie 4.0 (RAMI 4.0) [28] organises DT integration around six layers, from asset to business, folding organisational and human considerations into the top-level business layer as an undifferentiated element rather than a distinct architectural concern. ISO 23247 [103] similarly defines a User Entity through which people interact with the DT, but specifies it mainly as an interface for applications and visualisation rather than as a locus of decision authority or accountability. The DT Consortium’s Capabilities Periodic Table [104] comes closer to acknowledging this gap, as successive versions have added governance-oriented capabilities such as trustworthiness and, more recently, responsibility and ethics. Even so, decision authority and organisational accountability remain absent as explicit architectural categories across all three frameworks, treated as an interface or business concern rather than as properties an architecture must specify.

That this gap recurs across three independently governed reference architectures, spanning a national research initiative, an international standards body, and an industry consortium, suggests the omission is not incidental to any single framework. It instead reflects a broader tendency within the field to treat DT architecture as a technical specification problem, defining how systems connect and exchange data, rather than as a decision-support problem, defining who acts on that data and under what authority.

5.3 Barriers to Automation

Since Grieves' [1] early conceptualization of DTs, DT research has largely pursued the ideal of increasingly accurate digital representations of physical assets. However, the present analysis indicates that this pursuit of representational fidelity can lead to a trap, in which increasing data volume and precision do not yield corresponding gains in value. Consistent with Moody's Law of Information [99], the findings show that information value arises from contextual relevance rather than sheer quality and quantity. This is reflected in the pursuit of automation.

Automational value imposes substantially stronger requirements than informational or transformational value. Whereas informational value primarily concerns the effective presentation of information, and transformational value retains a human decision maker within the process, automational value requires the DT to support decisions and actions with minimal human intervention. This creates three interrelated requirements, as highlighted in Section 4.3.2. These requirements extend beyond technical system performance to include the characteristics of the decision itself and the organisational context in which automation is deployed.

As automation becomes an increasingly prominent objective in DT research and practice, these findings highlight that its feasibility cannot be assessed solely in terms of technical capability or data availability. Rather, automational value depends on the interaction between data reliability, decision characteristics, and organisational risk tolerance. This shifts the focus from asking whether a DT *can* automate a decision to whether the decision is sufficiently reliable, deterministic, and low-risk for the organisation to *allow* it to do so - an area that purely technical analyses cannot capture.

5.4 Role of Artificial Intelligence in Decision Support Systems

Recent developments suggest that Artificial Intelligence (AI) may increasingly blur the boundaries between the DSS mechanisms identified in this review. For example, one corpus study describes a logistics DT that uses natural-language interaction to allow operators without specialist modelling expertise to query and steer the system directly [88]. Such interfaces may reduce the expertise required to use knowledge-driven DSSs, potentially changing the relationship between the user and the underlying decision-support mechanism. These developments raise an important classification question: when AI changes how a user interacts with a DT, does it change the underlying decision-support mechanism, or only the interface through which that mechanism is accessed? The distinction matters because the review's framework classifies mechanisms according to how decision support is generated, whereas AI may increasingly change how that support is presented and acted upon.

The question also matters for evaluation. DT-based DSSs have traditionally been evaluated using technical measures such as model accuracy and synchronisation latency. As AI increasingly mediates interactions between decision makers and DTs, evaluation may also need to consider whether the system preserves the user's understanding of the decision, the transparency of the reasoning process, and accountability for the resulting action. A further open question follows from the mechanism-decision level pattern in Section 4.4.2: operational decisions are, over time, the raw material that tactical decisions are based on, yet the data- and communication-driven mechanisms

that dominate operational decision support are significantly less present at the tactical level. What currently prevents that operational data from being aggregated into tactical insight, and whether AI-mediated interfaces close or widen that gap, are directions for the research agenda that this review opens.

6. Limitations

Several methodological limitations, which have been considered when interpreting the findings and drawing conclusions, are acknowledged:

1. Although the search spans four databases (Scopus, Web of Science, IEEE Xplore, and ScienceDirect), other databases and grey literature such as industry reports and white papers were not searched, which may have limited the capture of practical implementations not published in academic venues.
2. The restriction to English-language publications may have introduced language bias, potentially excluding relevant research published in other languages.
3. Publication bias toward positive findings may affect the overall picture of DT effectiveness in decision-support contexts.
4. Each study was coded against a single, primary category per classification dimension (Section 3.6). Where a study addressed more than one decision level, mechanism, or value type, only the most substantively developed was recorded, so the analysis may understate the prevalence of multi-purpose DT implementations and of hybrid mechanisms.
5. The statistical associations reported in Section 4.4 are correlational: they establish which configuration-outcome combinations co-occur often across the published literature, not that a given configuration causes a given outcome.
6. Three of the ten pairwise associations tested in Section 4.4 (all involving industry) drew on contingency tables with more than 20% of cells below the expected-count threshold for a reliable chi-square approximation; these results should be treated as indicative rather than precise.
7. The Cochran-Mantel-Haenszel confound check in Section 4.4.4 was limited to the six industry categories present in the corpus, several of them small, which limits its power to rule out confounding conclusively.
8. The organisational-context criterion (C4) was operationalised through organisational-entity terms in titles, abstracts, and keywords (Section 3.2); studies that address organisational decisions in purely technical language may therefore have been excluded.
9. Requiring “digital twin” in the title (C3) favours precision over recall and may have excluded studies in which a DT is central to the work but not named in the title.

7. Conclusion

This systematic review of 299 studies makes four contributions. First, it develops a four-dimensional classification framework comprising abstraction level, DSS mechanism, decision level, and value type. This framework operationalises DTs as DSSs and addresses the limited attention given to decision support in previous DT classification research. Second, it shows that DSS mechanisms differ systematically in their information flows and human-in-the-loop roles. Model-driven systems delegate more of the reasoning process, whereas knowledge-driven systems retain greater involvement from decision makers. Third, it demonstrates that value realisation depends

on organisational conditions, not technical capability alone. Automational value is rare across the corpus, concentrated in model-driven DSSs, and further constrained by governance requirements. Transformational value, meanwhile, remains a human-implemented outcome that DTs can enable but cannot execute independently. Fourth, it shows that model-driven mechanisms are significantly under-represented in strategic decision support, and that component-scope DTs are similarly constrained, a pattern that retains its direction when industry composition is held constant. These findings reveal organisational limitations that purely technical analyses cannot capture.

Together, these findings establish that DT value depends on organisational alignment rather than technical sophistication alone. For practitioners, this emphasises that DT configuration should be treated as an explicit design decision linked to the intended decision type, data reliability should be established before automation is attempted, and action logging should also be prioritised to prevent informational decay. For researchers, the findings highlight the need to investigate the organisational and infrastructural conditions that enable DT value. These include governance structures, data trustworthiness, and the evolving role of AI in mediating human-DT interaction. Such factors ultimately determine what a DT's technical capabilities can achieve in practice.

Declaration of Generative AI and AI-assisted Technologies in the Manuscript Preparation Process

During the preparation of this work the author(s) used Claude AI in order to adjust the plot sizes, axes and font sizes for some of the figures via Python. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

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