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Digital Twin in Open-Pit Mining: A Review and Maturity-Based Assessment of Deployment and Operational Reality

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ABSTRACT

Digital twin (DT) technology is increasingly positioned as a transformative framework for cyber-physical integration in open-pit mining; however, its actual maturity and operational deployment remain unclear. This study presents a systematic review of 120 publications (2016–2026) to critically evaluate DT applications across exploration, extraction, safety management, and autonomous operations. A key contribution is the development of a five-level Digital Twin Maturity Model (DT-M²), which classifies systems as Digital Models (L0), Digital Shadows (L1), Basic Digital Twins (L2), Intelligent Digital Twins (L3), and Autonomous Digital Twins (L4). Application of this framework reveals that 56.7% of studies meet the minimum criteria for digital twins (L2–L4), although most operate at early-stage functionality, and only 10.8% demonstrate fully autonomous capabilities. Quantitative evidence from case-specific deployments indicates substantial but context-dependent performance improvements, including up to 44% increases in excavator output, 98.64% resource utilisation, and 40% reductions in slope risk management costs. However, these outcomes are not generalisable across the sector and are concentrated in highly instrumented operations. The review further identifies systematic overstatement in the literature, including misclassification of digital models and shadows as digital twins (43.3% of studies) and the extrapolation of site-specific performance metrics to industry-wide expectations. To bridge the gap between research and practice, a Digital Twin Adoption Roadmap is proposed, outlining phased implementation pathways, capability milestones, and indicative investment requirements. Critical limitations are also identified, including geological data constraints, lack of standardised architectures, cybersecurity vulnerabilities, and workforce skill gaps. This study provides a structured, evidence-based assessment of the current state of digital twins in open-pit mining, offering both a rigorous classification framework and practical guidance for future research, investment, and deployment.

1. Introduction

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Open-pit mining accounts for approximately 85% of global mineral production and remains marked by three persistent operational challenges: safety incidents, including slope failures and equipment accidents, that cause hundreds of fatalities annually; operational inefficiencies driven by suboptimal equipment utilization and reactive maintenance; and environmental impacts associated with land disturbance and contaminated drainage [1,2]. The February 2023 Xinjing open-pit collapse in Inner Mongolia, which killed 53 workers, illustrates the scale of the slope-failure hazard that motivates real-time monitoring in surface mining [3]. Pre-2016 foundational work, including Peck & Gray [4], Li & Song [5], and Du [6], is cited here for historical context only and was not included in the systematic review dataset. Digital twin conceptual frameworks relevant to mining were further elaborated by Lee [7], Rasheed *et al*. [8], and Al-Ali *et al*. [9]. Digital twin (DT) technology has been proposed as a cross-cutting solution to these challenges, and the volume of published research has grown from fewer than five papers per year before 2020 to 26 papers in 2025 alone. However, the rapid growth of this literature is accompanied by conceptual imprecision: many studies labeled as "digital twin" research deploy systems that are, more accurately, digital models or digital shadows. This conflation inflates perceived adoption and capability and is a critical flaw that this review explicitly addresses.

1.1 Digital Model, Digital Shadow, and Digital Twin: A Critical Distinction

The terms digital model, digital shadow, and digital twin are frequently used interchangeably in the mining literature but refer to fundamentally different levels of cyber-physical integration. As shown in Table 1, this review adopts the following definitions, aligned with Grieves [10], Boschert & Rosen [11], and the formal taxonomy of Kritzinger *et al*. [12], as well as complementary IoT-oriented definitions from Rasheed *et al*. [8] and Al-Ali *et al*. [9].

Table 1
Definitional distinction between Digital Model, Digital Shadow, and Digital Twin

Concept	Data Flow	Real-time Sync.	Feedback to Physical	Mining Example
Digital Model	None	No	No	Static block model, geological map
Digital Shadow	Physical → Virtual	Yes (one-way)	No	IoT sensor dashboard, equipment telemetry display
Digital Twin	Physical ↔ Virtual	Yes (bidirectional)	Yes (active control)	Slope warning system with automatic blast delay, autonomous haulage DT

A Digital Model is a static representation with no automatic connection to operational data. A Digital Shadow receives real-time data from physical sensors but does not feed commands or updated parameters back to the physical system. A Digital Twin, by the strict definition adopted here, establishes a bidirectional, continuously synchronised link: data flow both from the physical to the virtual (for model updating) and from the virtual to the physical (for control or decision output). This bidirectionality is the defining characteristic and the primary source of DT value over conventional digital modelling. Applying these definitions rigorously to the 120 included studies, 68 studies (56.7%) meet the minimum bidirectional definition of digital twins (L2–L4); 31 (25.8%) are digital shadows

(L1); and 21 (17.5%) are digital models (L0). This classification is made explicit in **Fig.** 5 (DT-M²), and informs the interpretation of all subsequent findings.

1.2 Review Objectives

The five specific objectives of this review are: (i) to introduce and apply a rigorous DT maturity taxonomy, the DT-M², that distinguishes digital models, digital shadows, and true digital twins across the 120 included studies; (ii) to evaluate state-of-the-art DT frameworks, architectures, and enabling technologies as deployed across the exploration-extraction-safety-autonomy continuum; (iii) to synthesise quantitative performance evidence from operational DT systems and compare DT-enabled outcomes with conventional mining practice; (iv) to identify and critically assess adoption barriers, failure modes, and overhyped claims in the current literature; and (v) to propose a structured adoption roadmap and prioritise research gaps to guide future investment and inquiry. The paper is organised as follows: Section 2 presents the search and screening methodology; Section 3 reports descriptive results; Section 4 introduces the two original contributions of this review; Section 5 delivers thematic synthesis; Section 6 provides critical analysis; Sections 7–13 address adoption barriers, chronological evolution, research gaps, agreements, implications, limitations, and conclusions.

2. Methodology
2.1 Review Protocol

This review followed a structured, pre-defined protocol covering record identification, screening, eligibility assessment, and evidence synthesis. Database searching returned 154 records and citation chaining contributed a further 88, giving 242 identified records; after removal of 28 duplicates, 214 unique records proceeded to title-and-abstract screening. Screening excluded 26 records, and the remaining 188 full-text articles were assessed against the eligibility criteria set out in Section 2.3. Of these, 68 were excluded: 22 were not relevant to open-pit or surface mining, 18 contained no digital twin content, 15 returned a low composite quality score (1–3), and 13 were duplicate publications or had non-recoverable full text. The final corpus therefore comprises 120 included studies, each classified by DT maturity level (L0–L4) during the eligibility assessment; studies described as digital twins by their source publications but not satisfying the definitional framework in Table 1 were reclassified accordingly. Recent reviews of DT systems in mining [13,14,15] confirm the rapidly expanding but terminologically inconsistent nature of the field, reinforcing the need for the structured classification approach adopted here. No ethics approval was required for this literature review.

2.2 Search Strategy

Database searches were conducted across Web of Science, Scopus, IEEE Xplore, Google Scholar, and SciSpace from 2016 to April 2026. Five search queries were formulated by progressive expansion from the primary research question. The exact search strings and per-database record counts are provided in Table 2.

Table 2
Search strings and record counts by database

Search String (abbreviated)	WoS	Scopus	IEEE	G. Scholar	SciSpace
"digital twin" AND "open-pit mining"	12	14	9	18	11
"digital twin" AND "open-pit" AND ("slope stability" OR "autonomous")	8	10	7	12	6
"digital twin" AND mining AND ("IoT" OR "edge computing" OR "AI")	14	16	12	22	9
"digital twin" AND mining AND ("safety" OR "hazard" OR "emergency")	9	11	8	15	7
("Mining 4.0" OR "smart mine") AND "digital twin"	6	8	5	9	4
Total (before deduplication)	49	59	41	76	37

2.3 Inclusion and Exclusion Criteria

Inclusion: (a) addresses DT, digital shadow, or digital model technology in mining contexts; (b) published 2016–April 2026; (c) peer-reviewed journal, conference proceedings, or credible technical report; (d) addresses at least one of: exploration, extraction, safety, or autonomous operations in open-pit or surface mining. Exclusion: (a) exclusively underground mining without surface relevance; (b) no quantitative or qualitative mining data presented; (c) duplicate publication; (d) non-recoverable full text.

2.4 Quality Assessment

Each included study was scored on three quality dimensions using a three-point scale (1 = Low, 2 = Medium, 3 = High): (i) Methodological rigour; (ii) Evidence strength (quantitative metrics, field deployment vs. simulation); (iii) Relevance specificity (direct vs. peripheral focus on open-pit DT). A composite score of 7–9 was classified as High Quality (n = 72), 4–6 as Medium Quality (n = 33), and 1–3 as Low Quality (excluded, n = 15 after full-text review). All classification and quality scoring were performed independently by two authors, with discrepancies resolved by consensus. Screening was conducted using Rayyan systematic review software. A pilot screening of 30 papers was performed before full screening to calibrate inclusion criteria and reduce inter-rater variability. Inter-rater agreement reached $\kappa = 0.81$ (substantial agreement).

Standardised extraction captured: DT maturity level (L0–L4), application domain, technological enablers, geographic context, quantitative performance metrics, and adoption barriers.

3. Results: Descriptive Summary

3.1 Publication Landscape

Fig. 1 presents the annual publication trend for the 120 included studies. Publication volume grew from a baseline of 1–3 papers per year (2016–2019) to a peak of 28 papers in 2024, with the period 2022–2026 accounting for 92 studies (76.7%). This acceleration reflects the convergence of three enabling conditions: the maturation of cost-effective IoT sensor platforms after 2019; the deployment of 5G networks in major mining regions between 2021 and 2023; and the publication of landmark operational studies, particularly from Chinese mining operations, that demonstrated large-scale DT feasibility [16,17,18]. The dominance of Chinese case studies in the high-impact performance sections reflects data availability and the scale of Chinese operational DT deployments rather than global deployment parity; significant deployments in other regions remain underrepresented in the peer-reviewed literature.

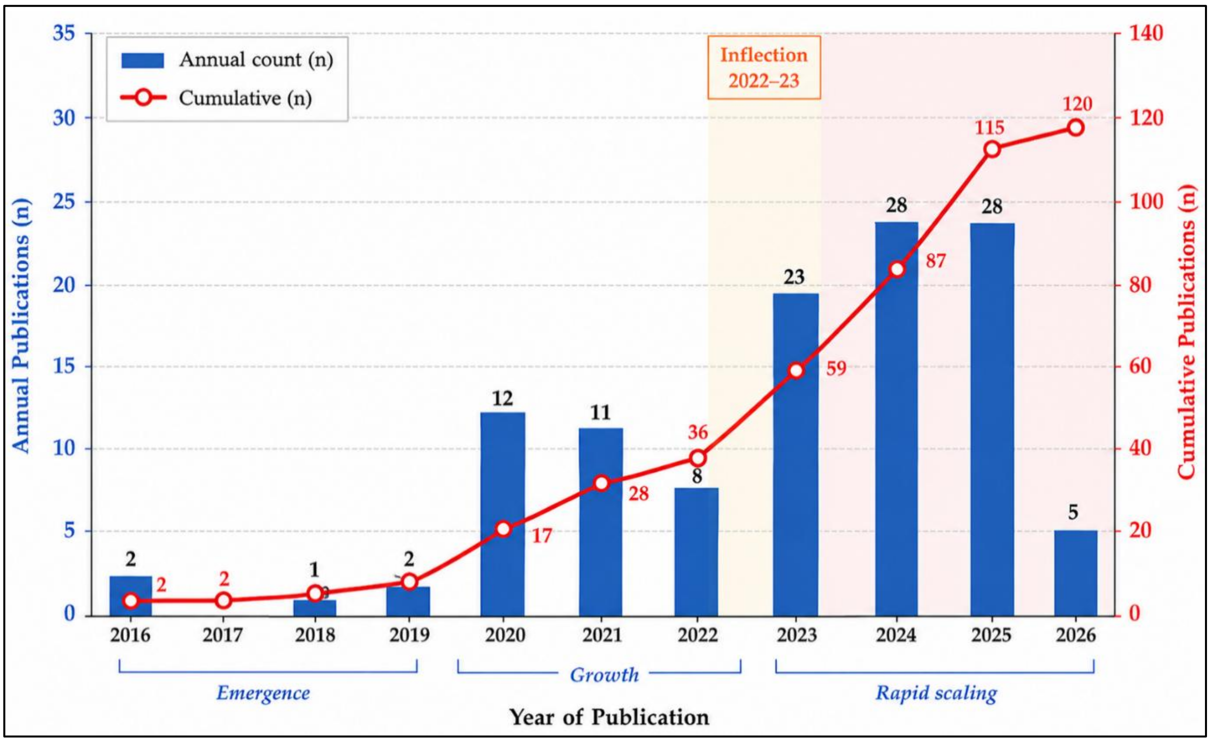

Fig. 1. Annual (blue bars) and cumulative (red line) publication counts for the 120 included studies, 2016–2026

3.2 Publication Types and Venues

Fig. 2 shows the distribution of publication types and the top venues. Journal articles constitute 81.7% of the corpus (n = 98), with Journal of Mine Automation (n = 8) and Applied Sciences (n = 7) as the most prolific venues. See also Agnusdei *et al*. [19], Duarte *et al*. [20], Farrelly & Davies [21], and Elmouttie & Dean [22] for systematic bibliometric overviews.

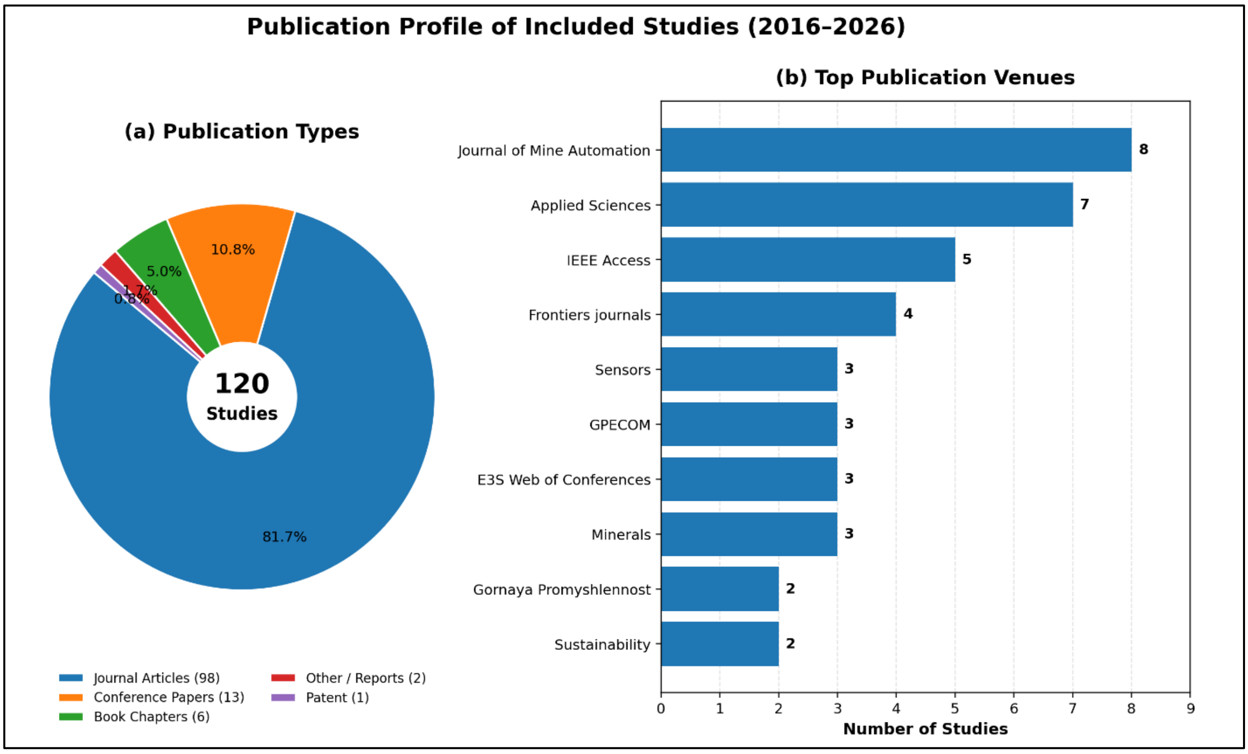

Fig. 2. (a) Distribution of publication types among the 120 included studies. Journal articles dominate (66%), reflecting the maturation of DT mining research beyond conference-stage work. (b) Top eight publication venues by study count.

3.3 Thematic Distribution

Fig. 3 presents the thematic distribution of studies across ten research categories identified through inductive coding. Digital Twin Frameworks and Real-Time Monitoring is the most prevalent theme (n = 28; 23.3%), followed by Autonomous and Intelligent Mining Systems (n = 20; 16.7%) and Safety Management and Hazard Detection (n = 18; 15.0%). The dominance of framework and monitoring studies over safety-critical applications confirms Duarte & Baptista's [23] observation that operational efficiency remains the primary commercial driver of DT adoption, with safety management receiving proportionally less targeted research investment despite its arguably greater social importance. Emerging themes include environmental and ESG-oriented DT applications [24,25,26] and AI-capability reviews relevant to mining contexts [27,28].

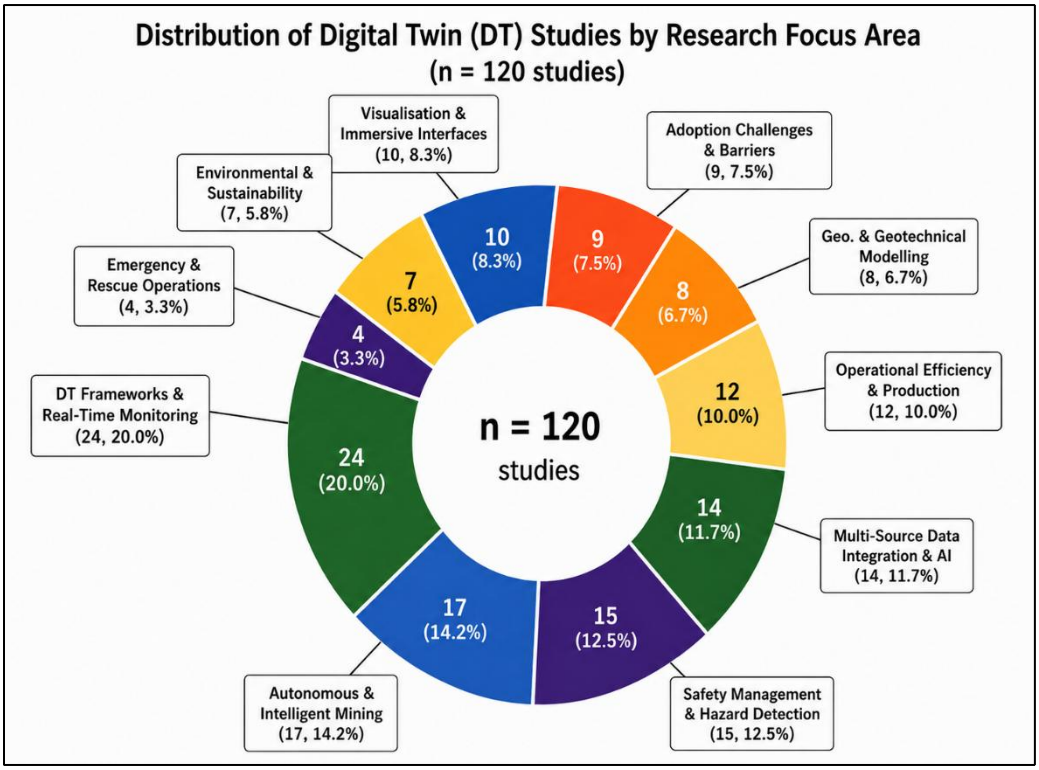

Fig. 3. Thematic distribution of the 120 included studies across ten research categories (donut chart; n values and percentages shown for each segment). The dominance of framework/monitoring studies (23.3%) over safety-critical applications (15.0%) reflects the commercially driven nature of current DT deployment, where efficiency gains offer clearer short-term ROI than safety improvements.

3.4 Geographic Distribution of Research Output

Fig. 4 maps the review corpus by the country of the first author's host institution. Attribution followed a single rule applied consistently: each study was assigned to one country only, that of the corresponding or first author's institution at the time of publication, so that the counts sum exactly to the 120 included studies and no study is double-counted across international collaborations. Where a paper had authors in several countries, for example the Australian–Chinese and Peruvian–Australian collaborations in the corpus, only the first author's country is counted, which means the map understates the true reach of collaborative work. Reference [3] is excluded from the map because it is cited in Section 1 as an illustrative incident and was not screened into the corpus.

Output is heavily concentrated. The 120 studies originate from just 22 countries, and the two leading contributors supply 63 studies between them (52.5%). China alone accounts for 46 studies (38.3%), which quantifies the observation made in Section 3.1 that Chinese work dominates the high-impact performance evidence, and confirms that this dominance reflects publication volume rather than global deployment parity. Russia contributes 17 studies (14.2%), concentrated in coal and mineral digitalisation programmes and published largely in regional Russian-language venues directly relevant to the language limitation stated in Section 12, since the true Russian-language output is almost certainly larger than the corpus captures. A secondary cluster comprises the established mining-research economies of Australia (8 studies, 6.7%), Canada (5, 4.2%) and the United States (4, 3.3%); their contributions skew toward review, framework and systems-engineering work rather than operational deployment case studies, which is consistent with the finding in Section 5 that verified performance metrics come disproportionately from Chinese operations.

Two features of the distribution require careful interpretation. First, Morocco's six studies (5.0%) place it sixth globally, but all six originate from a single research group working on one experimental open-pit facility; the national figure therefore reflects the productivity of one laboratory rather than broad-based national capacity, and should not be read as evidence of widespread Moroccan DT deployment. Second, and more consequentially, the map exposes a systematic evidence gap in the regions where open-pit mining is most economically significant. Chile and Peru together contribute three studies (2.5%) despite hosting the world's largest copper operations, and Sub-Saharan Africa, including South Africa, Ghana, the Democratic Republic of the Congo and Zambia, which collectively dominate global platinum, gold, cobalt and copper production, contributes none. This review cannot determine whether that absence reflects genuinely low DT adoption in those jurisdictions or the documentation of such work in industry and consultancy channels that fall outside the peer-reviewed literature. Either way, it means the evidence base underpinning current DT claims is drawn from a narrow and unrepresentative slice of the global mining industry, and conclusions about DT maturity should not be generalised to the sector as a whole.

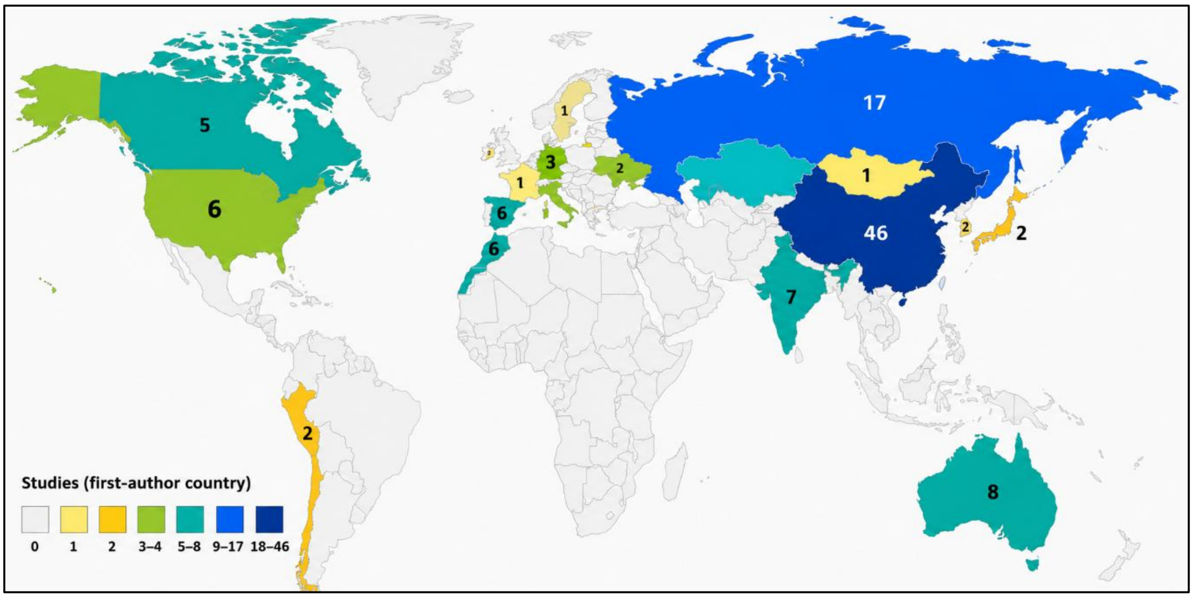

Fig. 4. Global distribution of the 120 included studies on digital twins in open-pit and surface mining, 2016–2026

4. Original Contributions: DT Maturity Model and Adoption Roadmap

4.1 The DT Maturity Model (DT-M²)

This review introduces the Digital Twin Maturity Model for Open-Pit Mining Operations (DT-M²), a five-level classification framework synthesised from the 120 included studies. The model, illustrated in **Fig.** 5, provides a structured taxonomy for assessing the current state and development trajectory of DT deployments. It distinguishes the following levels:

Level 0 (Digital Model): Static virtual representations with no real-time data connection. These include conventional block models, geological maps, and offline simulation environments. They provide no operational feedback and are not DTs by any rigorous definition. 21 of the 120 included studies were reclassified to this level (e.g., Duarte & Baptista [23]; Nagovitsyn & Stepacheva [29]).

Within-period L0 examples include Nagovitsyn & Stepacheva [29], Kunytska [30], and Quelopana *et al*. [31].

Level 1 (Digital Shadow): Real-time unidirectional data flow from physical to virtual. Sensor data continuously updates the virtual model, enabling monitoring and visualisation, but no automated feedback to physical systems occurs. 31 studies operate at this level (e.g., Temkin *et al*. [32]; Hodgkinson & Elmouttie [33]). Additional L1 studies include Elmouttie & Dean [22], Koteleva *et al*. [34], Wang & Lu [35], Gu *et al*. [36], and Ge & Zhang [37].

Level 2 (Basic Digital Twin): Bidirectional synchronisation with basic simulation capability. The virtual model can issue alerts, recommendations, or simple control outputs to the physical system. 28 studies achieve this level (e.g., Elbazi *et al*. [38]; Svadkovsky [39]; Cheng & Hou [40]). Further L2 examples: Miao *et al*. [41], Servin *et al*. [42], Khakulov *et al*. [43], and Virando *et al*. [44].

Level 3 (Intelligent Digital Twin): AI-enhanced DT with predictive and prescriptive analytics. The virtual model uses machine learning to anticipate future states and prescribe optimised actions, with closed-loop feedback to physical operations. 27 studies reach this level (e.g., Yu & Yang [45]; Dong *et al*. [46]; Yao *et al*. [47]; Bimpong *et al*. [48]). Additional L3 studies include Xing [49], Wang *et al*. [50], Huang *et al*. [51], and El Hiouile *et al*. [52].

Level 4 (Autonomous Digital Twin): Self-evolving DT with full bidirectional autonomous control. The virtual model continuously self-calibrates, controls physical assets without human intervention, and adapts to novel conditions. Only 13 studies achieve this level (e.g., Chen *et al*. [16]; Chen *et al*. [17]; Liu *et al*. [18]). Additional L4 systems include Lei *et al*. [53], Rylnikova [54], and Song *et al*. [55].

This review contributes by making explicit that the mining DT literature is substantially less mature than headline claims suggest. A total of 68 studies (56.7%) meet the minimum criteria for digital twins (L2–L4), though most remain at early-stage implementations with limited autonomy. Only 10.8% represent fully autonomous systems (L4).

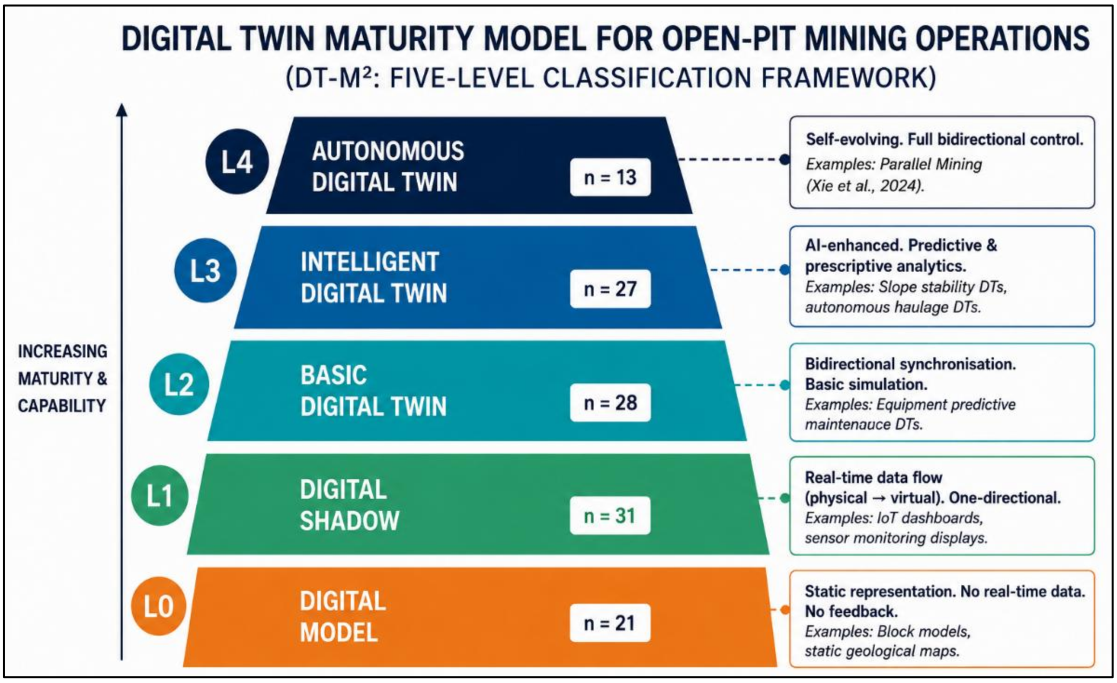

Fig. 5. The Digital Twin Maturity Model for Open-Pit Mining (DT-M², original contribution).

Five levels are arranged as a pyramid, with base width proportional to the number of studies at each maturity level. Level badges (L0–L4) identify each tier. Study counts (n) are shown for each level. The model clarifies that the majority of reviewed studies operate at L1 (Digital Shadow) or L2 (Basic DT) levels, and only 13 of 120 studies (10.8%) constitute fully autonomous DT systems.

4.2 The DT Adoption Roadmap (DT-AR)

Fig. 6 presents the Digital Twin Adoption Roadmap (DT-AR), an original framework synthesised from the evidence base of 120 studies and structured around the four DT-M² transition points. **Phase 1** (0–12 months; target: L0–L1) focuses on deploying foundational sensor infrastructure and achieving real-time data visibility at an estimated cost of $0.5–2 million for a mid-scale open-pit operation. **Phase 2** (12–24 months; target: L1–L2) integrates edge computing and basic automation, with predictive maintenance as the primary early-return application [56] (estimated cost: $2–5 million). **Phase 3** (24–48 months; target: L2–L3) introduces AI-enhanced analytics, slope stability DTs, and cross-system data fusion (estimated cost: $5–15 million). **Phase 4** (48–72 months; target: L3–L4) deploys autonomous vehicle fleets and self-evolving DT architectures (estimated cost: $15 million and above). These cost estimates are derived from reported implementation figures in Chen *et al*. [16], Svadkovsky [39], and Lei *et al*. [53], and should be treated as indicative rather than prescriptive.

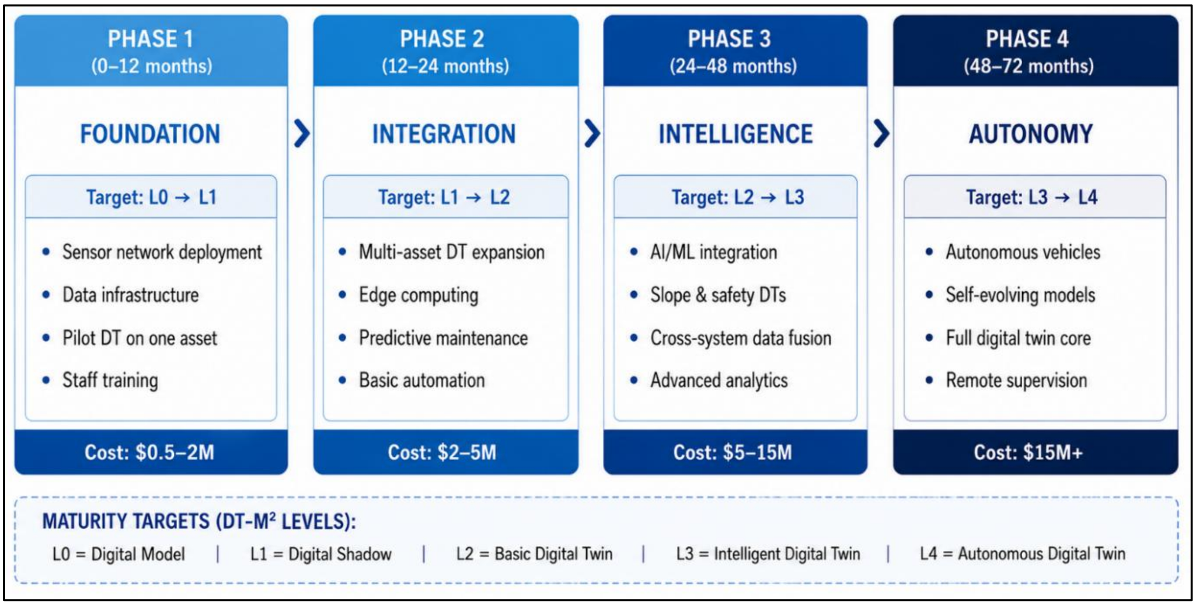

Fig. 6. Digital Twin Adoption Roadmap for open-pit mining operations (DT-AR, original contribution)

5. Thematic Synthesis and Critical Analysis

5.1 DT Frameworks and Architectures

Fig. 7 presents the canonical four-layer DT architecture synthesised from the reviewed literature. The architecture comprises: a physical sensing layer (IoT sensors, GPS, radar, UAVs); a data acquisition and edge computing layer (5G/6G transmission, edge pre-processing); a digital twin core (physics-based simulation, AI/ML engines); and an analytics and application layer (dashboards, AR/VR interfaces, autonomous control outputs). This architecture appears in various forms across 28 framework studies [38,53,57]. Lei *et al.* [53] demonstrated that separating edge pre-processing from cloud-level simulation reduced system latency below 100 ms for real-time fault detection, a threshold identified as necessary for closed-loop equipment control. El Bazi *et al*. [57] extended the basic architecture with a compositional design pattern enabling modular addition of new asset types without full system redesign. Related framework studies confirming these architectural principles include Farrelly & Davies [21], Miao *et al*. [41], Aziz *et al*. [58], Ghahramanieisalou & Sattarvand [59], Yusupbekov *et al*. [60], El Bazi *et al*. [61], and El Bazi *et al*. [62,63]. Layer 1 (Physical): IoT sensors, GPS, radar, UAVs, and geotechnical instruments. Layer 2 (Data): Edge computing nodes with 5G/6G transmission. Layer 3 (Digital Twin Core): Physics-based models, AI/ML engines, calibration modules. Layer 4 (Applications): Predictive maintenance, AR/VR interfaces, autonomous control. The bidirectional feedback arrow between layers is the defining characteristic that distinguishes a true DT (L2–L4) from a Digital Shadow (L1).

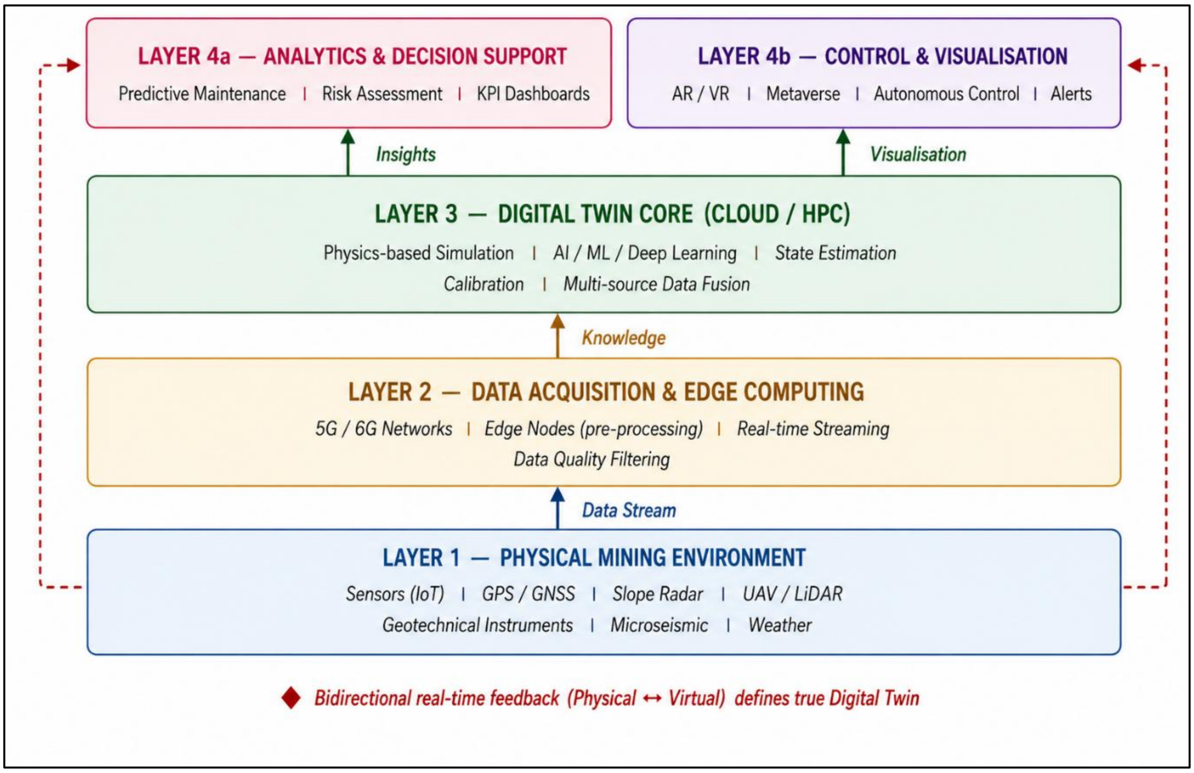

Fig. 7. Four-layer DT architecture for open-pit mining, synthesised from 28 framework studies.

5.2 Extraction and Production Optimisation: Verified Performance Metrics

Table 3 summarizes the quantitative performance metrics reported across production optimisation studies. These figures are directly traceable to their source publications and should not be generalised beyond the operational contexts in which they were measured.

These metrics must be interpreted with three caveats. First, several studies [18,47] report figures from deployments at large Chinese coal mines with high automation investment, and these gains are unlikely to replicate directly in smaller or less capitalised operations. Second, the 21% EBITDA and 96% free cash flow figures from Svadkovsky [39] are reported without the baseline production data needed to assess causality. Third, none of the reviewed studies provide randomised or controlled comparisons with conventional operations; all efficiency gains are reported relative to pre-DT historical baselines. Comparable production DT studies reporting quantitative outcomes include Khakulov *et al.* [43], Zhang *et al.* [64], Fu *et al.* [65], Duarte *et al.* [66], Cui *et al.* [67], Liu *et al.* [68], Xing *et al.* [69], Lv *et al.* [70], Wang *et al.* [71], and Lotsu *et al.* [72].

Table 3
Verified quantitative performance metrics from production optimisation studies

Study	DT Level	Key Metric	Value Reported	Operational Context
Liu *et al*. [18]	L3	Excavator output increase	44%	Open-pit coal, unmanned multi-machine, China
Liu *et al*. [18]	L3	Excavator idle time reduction	92%	Same deployment as above
Yao *et al*. [47]	L3	Resource utilisation	98.64%	Intelligent ore management system, China
Svadkovsky [39]	L2	EBITDA increase	21%	Extractive industry DT deployment, Russia
Svadkovsky [39]	L2	Free cash flow growth	96%	Same deployment as above
Chen *et al*. [16]	L4	Operational uptime	24/7	Parallel intelligence, multiple mines, China
Cheng & Hou [40]	L2	Risk management cost reduction	40%	Open-pit slope DT, China
Kunitskaya *et al*. [73]	L2	Reserve estimation accuracy	+15–20%	3D geological DT, Ukraine
Dong *et al*. [46]	L3	False alarm reduction	Substantial	Cloud-based LSTM slope monitor, China
Lei *et al*. [53]	L3	Control loop latency	<100 ms	Multi-machine coordination DT, China

5.3 Safety Management: Evidence and Limitations

Slope instability is the highest-consequence safety hazard in open-pit mining, and DT-based slope monitoring is one of the most active and technically credible application areas in the reviewed literature. Cheng & Hou [40] demonstrated that integrating empirical geomechanical models with six data streams within a DT framework improved slope movement prediction accuracy and reduced proactive risk management expenditure by 40% over 24 months at a Chinese open-pit coal mine. Dong *et al.* [46] deployed a cloud-based LSTM neural network DT that reduced false alarm rates substantially while maintaining detection sensitivity, a critical balance in safety systems where alarm fatigue from false positives directly reduces worker compliance with genuine alerts. Wen *et al.* [74] designed a mine-site emergency rescue DT that reduced coordination time in simulated mine-accident scenarios through automated personnel tracking, dynamic route optimisation, and real-time dispatch of rescue resources. Kamalakannan *et al.* [75] demonstrated a federated learning DT architecture for fire risk prediction that achieved high accuracy while preserving data privacy across distributed mining sites. Additional safety DT studies in this review include Gu *et al*. [36], Virando *et* *al*. [44], Tripathi & Patwal [76], Cacciuttolo *et al*. [77], Golubeva *et al*. [78], Song *et al*. [79], Shu-yu *et al*. [80], and Mahmoudi Kouhi *et al*. [81].

Notwithstanding these advances, three safety application gaps remain. First, emergency response DTs are represented by only five studies [74,75,82], and none provides a field-validated deployment in a real emergency scenario. All validation is simulation-based. Second, worker tracking and personal safety monitoring are addressed by only two studies. Third, cybersecurity for safety-critical DT systems is identified by Zio & Miqueles [82] as an unresolved priority: the bidirectional control loop that defines L2+ DTs creates an attack surface through which a compromised system could issue erroneous commands to physical equipment with potentially catastrophic consequences.

5.4 Autonomous Mining: Verified Deployments and Remaining Constraints

Fig. 8 compares five DT application categories across six performance dimensions, illustrating that Autonomous DTs achieve the highest scores on efficiency, safety, and autonomy dimensions but the lowest scores on adoption ease. The most comprehensive field deployment described in the reviewed literature is the Parallel Mining framework of Chen *et al*. [16], deployed across multiple open-pit mines in China. The framework integrates self-evolving DTs for six autonomous systems: unmanned excavators, haul trucks, drilling rigs, blasting systems, auxiliary vehicles, and mine management, with stable 24/7 operation reported.

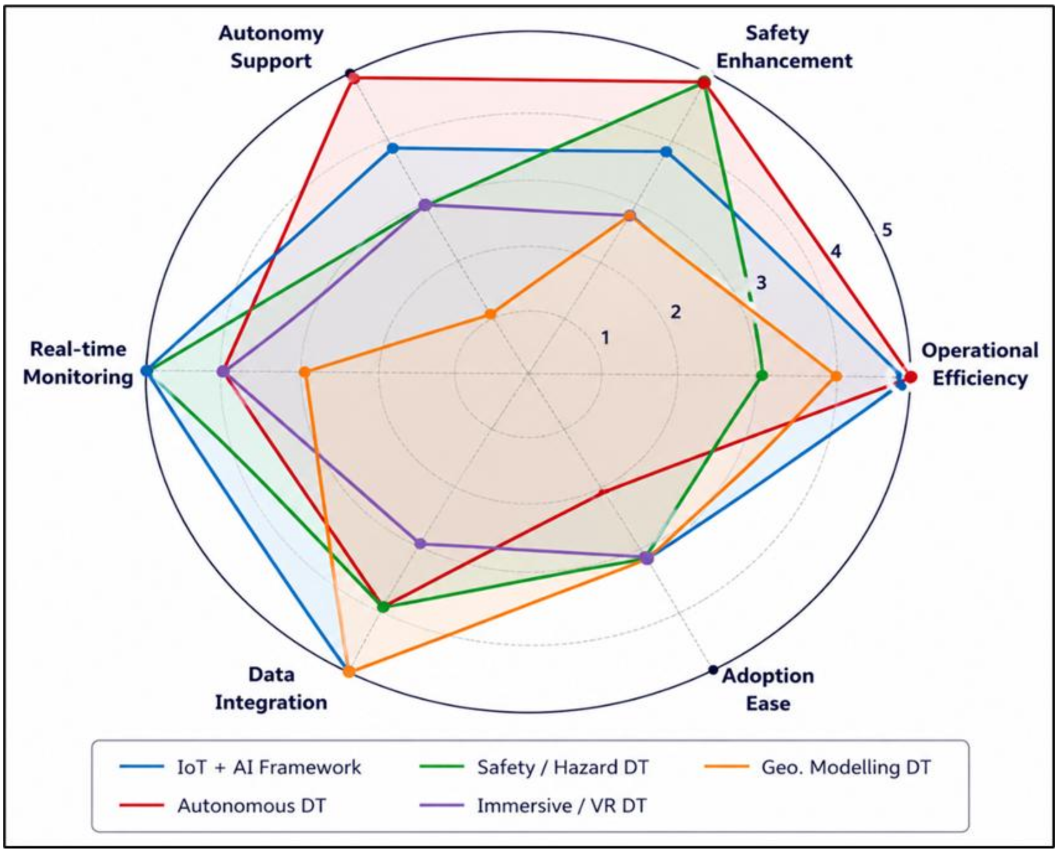

Fig. 8. Radar chart comparing five DT application categories (IoT+AI Framework, Autonomous DT, Safety/Hazard DT, Immersive/VR DT, Geo. Modelling DT) across six performance dimensions (scale: 1 = Low, 5 = High). Autonomous DT systems achieve the highest combined scores but face the greatest adoption barriers (lowest “Adoption Ease” score). Safety/Hazard DTs show high safety enhancement but limited autonomy, reflecting their monitoring rather than control function.

Chen *et al.* [17] described the "digital quadruplet" architecture, extending the DT concept to four interacting entities (physical, virtual, service, and data), deployed in unmanned coal mine operations. Liu *et al.* [18] specifically addressed the collaborative production scheduling problem, demonstrating that AI-optimised real-time scheduling under DT situational awareness achieved the 44% output increase and 92% idle time reduction referenced in Table 3.

Full autonomy faces four documented constraints. First, environmental complexity: geological variability, unpredictable weather, and dynamic blasting schedules create operational scenarios not fully validated at all mine sites [16]. Second, scalability: current systems require extensive site-specific data collection and model training [16]. Third, economic viability: no reviewed study provides a full cost-benefit analysis of autonomous DT deployment below a defined profitability threshold. Fourth, regulatory readiness: no regulatory framework specifically governs autonomous DT systems in mining in any jurisdiction covered by the reviewed literature. Autonomous and semi-autonomous DT studies providing additional evidence of these constraints include Lei *et al*. [53], Ai *et al*. [83], Leung *et al*. [84], Samaei *et al*. [85], Li *et al*. [86], Klebanov *et al*. [87], Umirzoqov *et al*. [88], You *et al*. [89], Miao *et al*. [90], and Liu [91].

5.5 Immersive Technologies and the Metaverse: Promise and Overhype

Twelve studies address AR/VR and metaverse integration with DTs. Patel *et al.* [92] proposed a dual-infrastructure DT with AR/VR control room interfaces powered by 6G networks. Liu *et al.* [93] introduced MetaMining, a metaverse-integrated mining environment where operators interact with digital replicas in real time. Acosta-Quelopana *et al.* [94] conducted an empirical technology acceptance study using SEM and found that perceived usefulness (not ease of use) is the dominant adoption predictor for AI-supported DTs in mining metaverse environments. However, a candid assessment of this literature reveals a pattern of overhype: the majority of metaverse and AR/VR DT studies present architectural proposals or early-stage prototypes without field deployment validation. The claim that metaverse-integrated DTs can manage open-pit mines is currently unsupported by operational evidence. Related immersive DT studies include Plavšić & Mišković (2024) and Liu *et al.* [95,96].

6. Critical Analysis: Limitations, Failure Modes, and Overhyped Claims
6.1 Where Current DT Systems Cannot Perform

The evidence base supports the following specific statements about the current boundaries of DT capability in open-pit mining:

(1) Current DT systems are limited in their ability to reliably represent subsurface geological variability at the resolution required for day-to-day mining decisions. Hodgkinson & Elmouttie [33] demonstrate that borehole data density is typically insufficient for reliable three-dimensional interpolation between sample points. Complementary geological DT limitations and partial solutions are documented in Kunitskaya *et al*. [73], Shu-yu *et al*. [80], Almenov *et al*. [97], Chen *et al*. [98], Cao *et al*. [99], Rahman [100], Kornilkov & Rybnikova [101], and Kunytska *et al*. [102].

(2) Current DT systems cannot be rapidly deployed at a new mine site without a substantial site-specific training and calibration period. Chen *et al*. [16] acknowledge this limitation directly: the Parallel Mining system required significant data acquisition before autonomous operation was stable enough for full deployment.

(3) Current DT systems cannot yet guarantee cybersecurity in adversarial environments. Zio & Miqueles [82] identify that the bidirectional control capability of L2+ DTs creates attack surfaces that existing industrial cybersecurity frameworks do not adequately address. Complementary safety gap analyses are provided by Li *et al*. [86], Ermakova *et al*. [103], Quansah *et al*. [104], He *et al*. [105], Luo *et al*. [106], and Li [107].

(4) Current DT systems for emergency rescue [74] have rarely been validated in real mine accident scenarios. All published validations are simulation-based. The gap between simulated and real emergency conditions, including communication failures, structural instability, and the psychological behaviour of rescue personnel, is not addressable by simulation alone.

(5) Current DT systems are unable, in isolation, to address the workforce skill gap. Galagedarage Don *et al*. [108] identify a severe shortage of personnel capable of operating and maintaining advanced DT systems in most mining jurisdictions.

6.2 Discrepancies Between Reported and Demonstrated DT Capabilities

Three categories of overstatement appear systematically in the reviewed literature. First, the use of the term "digital twin" for systems that are, by rigorous definition, digital shadows or digital models; this conflation appears in approximately 43.3% of reviewed studies (n = 52) and inflates apparent DT adoption rates. Second, the generalisation of site-specific performance metrics particularly the 44% output increase (Liu *et al.*, 2024 [18]), 98.64% resource utilisation (Yao *et al.*, 2025 [47]), and 21% EBITDA improvement (Svadkovsky, 2024 [39]) to the mining sector at large; each figure was obtained at a specific mine with specific characteristics and is not transferable without adjustment. Third, the characterisation of metaverse and AR/VR DT systems [93,95,96] as operational technologies when the published evidence base describes only prototypes and acceptance surveys.

6.3 Contradictions Between Studies

The reviewed literature contains three significant areas of contradiction. First, on DT maturity: Chen *et al*. [16] and Chen *et al.* [17] report operational autonomous systems deployed at scale in China, while Qu *et al.* [15] and Duarte & Baptista [23] characterise the global sector as early-stage and predominantly pre-deployment. Both assessments are accurate within their geographic and organisational contexts. Second, on the safety-efficiency priority: safety-focused studies [74,82] argue that safety is the most compelling underinvestment area, while efficiency-focused studies [18,39] demonstrate that efficiency gains provide the clearest commercial ROI. Third, on geological DT feasibility: Hodgkinson & Elmouttie [33] argue that geological complexity fundamentally limits DT fidelity, while Cao *et al.* [99] and Cheng & Hou [40] demonstrate substantially improved geological prediction accuracy using multi-source data fusion in DT frameworks.

7. Adoption Barriers and Enabling Factors

Fig. 9 presents the frequency of adoption barriers and enabling factors identified across the 120 included studies, indicating that economic and technical barriers substantially outweigh enabling factors in most deployment contexts outside China. Economic costs are the most frequently cited barrier (n = 20 studies), with implementation costs for L3–L4 systems estimated at \$5–\$15 million per mine [39,53]. Technical complexity (n = 18) and data integration challenges (n = 16) are the second and third most frequent barriers. The absence of standardised DT architectures and protocols (n = 10 studies) amplifies all other technical barriers. Communication technology advances (5G/6G) and AI capability improvements are identified as the most significant enabling factors. Acosta-Quelopana *et al.* [94] provide empirical evidence that perceived usefulness, not ease of use, is the dominant predictor of DT adoption intention; the digital twin standardisation landscape across ISO, IEC, ITU and IEEE is reviewed by Wang *et al*. [109]. Further evidence of barriers and enablers is documented in Elbazi *et al*. [38,62,63], Wang *et al*. [50], El Hiouile *et al*. [52], El Bazi *et al*. [61], Song *et al*. [79], Mahmoudi Kouhi *et al*. [81], Nikitenko *et al*. [110], Noskov *et al*. [111], Sun *et al*. [112], Chand *et al*. [113], Gulin *et al*. [114], and Zheng *et al*. [115].

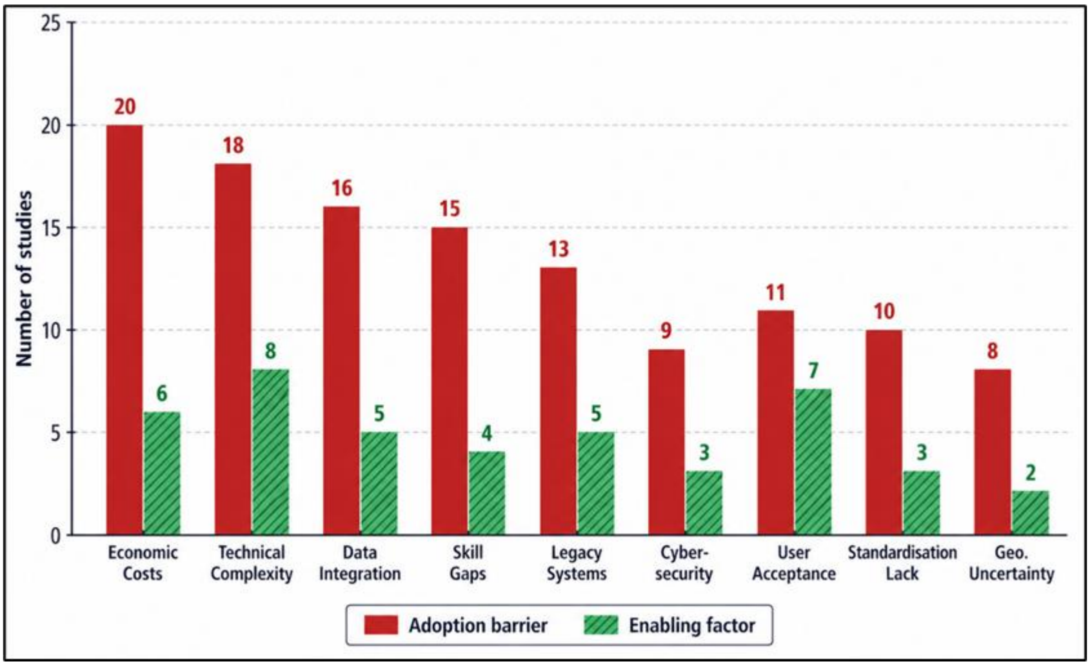

Fig. 9. Quantitative comparison of adoption barriers (red bars) and enabling factors (green hatched bars) across the 120 included studies. Both axis scales represent the number of studies that explicitly identify each factor. Economic costs represent the most-cited barrier (n = 20). Communication technology advances (5G/6G) and AI capability improvements are the most cited enablers, reflecting a technology-push dynamic in current DT adoption.

8. Chronological Evolution

Fig. 10 presents the temporal evolution of DT research as a bubble timeline, with bubble size proportional to annual publication volume, demonstrating an accelerating maturation trajectory. The timeline confirms four distinct phases: foundational digital modelling (2020–2021); industrial applications and AI integration (2022–2023); intelligent and autonomous systems (2024); and advanced architectures with sustainability focus (2025–2026). The progression from L0–L1 systems in the foundational phase to L3–L4 systems in the advanced phase demonstrates that the field has compressed a 20-year industrial automation maturity trajectory into approximately six years [116,117], driven by the simultaneous availability of IoT platforms, 5G connectivity, and cloud AI services [108,116]. This trajectory is corroborated by the chronological sequence of studies in this review: foundational work by Duarte *et al*. [20], Quelopana *et al*. [31], Ge & Zhang [37], Servin *et al*. [42], Duarte *et al*. [66], Semenov *et al*. [118], Efimov & Efimova [119], and Liang *et al*. [120] preceded the mid-phase contributions of Huang *et al*. [51], Liu *et al*. [68], and Xu *et al*. [121], with the most recent wave represented by Chand *et al*. [113], Gulin *et al*. [114], Zheng *et al*. [115], Xing [122], and Rakhima *et al*. [123].

Bubble size is proportional to annual publication volume; numbers inside bubbles indicate total papers for that year. Phase labels above bubbles identify the dominant research direction for each period. The rapid progression from foundational modelling (2020–2021) to advanced autonomous architectures (2025–2026) in just six years reflects the accelerating maturation of enabling technologies rather than steady incremental progress.

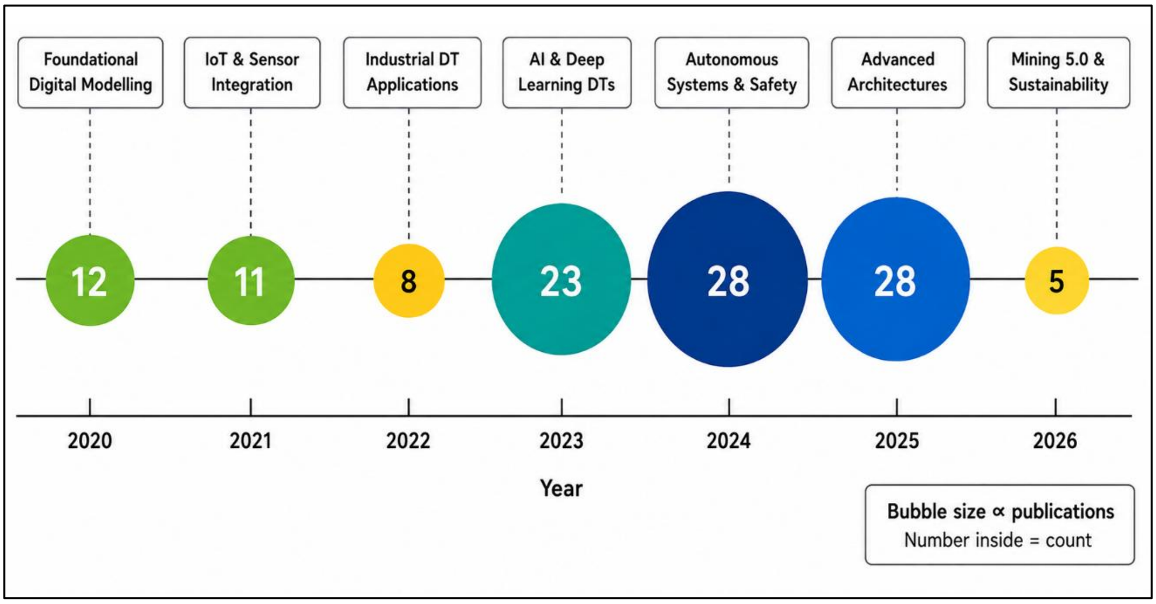

Fig. 10. Bubble timeline of the evolution of DT research in open-pit mining (2020–2026).

9. Research Gaps and Future Directions

Table 4 presents the nine prioritised research gaps identified through systematic synthesis, with each gap linked to specific evidence from the reviewed literature.

Table 4
Prioritised research gaps, future research directions, and supporting evidence

Priority	Gap	Future Research Direction	Key Evidence	Timeframe
High	Standardised DT architectures	Open API standards and data models for mining DTs; pilot cross-vendor integration	Qu *et al*. [15]	1–3 years
High	Adaptive autonomous intelligence	Foundation AI models adaptable to new mine sites without full retraining	Chen *et al*. [16]; Liu *et al*. [18]	3–5 years
High	Geological data integration	Probabilistic geological DTs with real-time uncertainty quantification	Hodgkinson & Elmouttie [33]	2–4 years
High	Cybersecurity frameworks	Adversarially robust DT architectures with mining-specific security protocols	Zio & Miqueles [82]	1–2 years
High	Safety-first DT design	Dedicated safety-critical DT design frameworks; systematic failure mode analysis	Duarte & Baptista [23]	2–3 years

High	Real-time multi-source fusion	Heterogeneous fusion with latency below 50 ms for safety-critical monitoring	Lei *et al*. [53]	1–3 years
Medium	Environmental/ESG integration	DT frameworks incorporating contamination monitoring and ESG reporting	Maté-González *et al*. [26]	3–5 years
Medium	Comprehensive cost-benefit analysis	Longitudinal ROI studies, including total cost of ownership and indirect benefits	Svadkovsky [39]	1–2 years
Medium	Operational AR/VR validation	Field-validated immersive DT for real-time operational control	Patel *et al*. [92]	2–4 years

10. Agreements and Divergences Across Studies

The reviewed literature converges on the following conclusions: (i) DTs provide measurable improvements over conventional monitoring and control systems when correctly implemented at L2 or above; (ii) multi-source sensor data integration is the defining technical challenge and capability of operational DTs; and (iii) adoption barriers economic, technical, and human are universally acknowledged across geographic contexts. Significant divergences exist in three areas, as documented in Table 5.

Table 5
Key areas of agreement and divergence across the 120 included studies

Criterion	Studies in Agreement	Studies in Divergence / Explanation
DT maturity	All studies: benefits increase with DT maturity level	China-based studies report L4 operational deployments [16]; European and North American studies report L1–L2 prototypes [14,15], reflecting genuine geographic differences, not methodological disagreement
Safety vs. efficiency priority	All: both domains benefit from DT	Safety studies argue DT safety is underinvested [82]; efficiency studies show stronger commercial ROI [18,39] different stakeholder perspectives rather than contradictory findings
Geological DT feasibility	All: geological uncertainty limits DT fidelity	Hodgkinson & Elmouttie [33]: fundamental constraints remain; Cao *et al*. [99]; Cheng & Hou [40]: multi-source fusion substantially reduces (not eliminates) limitations
Adoption timeline	All: barriers exist and slow adoption	Chinese studies describe accelerating deployment; most others characterise the sector as nascent, consistent with real geographic disparities in capital investment and policy support

11. Theoretical and Practical Implications

11.1 Theoretical Implications

This review advances theory in three areas. First, the DT-M² maturity model provides a formal taxonomy for classifying DT research that exposes the widespread conflation of digital models, digital shadows, and true digital twins in the mining literature. This taxonomy has direct implications for how progress in the field is assessed: by the DT-M² classification, genuine operational DT deployment (L2–L4) is present in 56.7% of reviewed studies (n = 68), though a significant share of source publications labelled as "digital twin" research were reclassified to L0 or L1 upon critical assessment. Second, the critical analysis of geological DT limitations [15,33] advances the theoretical understanding of the boundary conditions within which physics-based simulation models can serve as reliable predictive tools in natural (as opposed to engineered) systems. Third, the identification of parallel intelligence [16,17] as a distinct L4 DT paradigm extends the conceptual vocabulary of DT theory beyond monitoring and simulation toward genuine cyber-physical co-adaptation. Related theoretical contributions on DT classification and maturity in mining contexts are provided by Agnusdei *et al*. [19], Kunytska [30], Kunitskaya *et al*. [73], and Kunytska *et al*. [102].

11.2 Practical Implications

For mining practitioners, the DT-AR adoption roadmap provides structured investment guidance aligned with demonstrated industry evidence. The near-term highest-return applications are equipment predictive maintenance (L2, cost $2–5M, demonstrable ROI within 12–18 months) [56] and slope stability monitoring with early warning (L2–L3, directly reduces the risk of slope failure incidents with documented cost reductions of 40% in risk management expenditure [40]). Autonomous haulage systems offer larger long-term returns but require $15 million-plus investment, multi-year deployment periods, and site-specific system adaptation. For technology developers, the standardisation gap is the highest-leverage intervention point: open DT data standards and interoperability protocols would simultaneously reduce integration costs, accelerate adoption, and enable the accumulation of cross-site operational data that is the prerequisite for adaptive autonomous intelligence. For policymakers and regulators, the cybersecurity and worker safety gaps identified in Section 6 require regulatory attention before further autonomous DT expansion in mining: clear safety case requirements for autonomous DT systems, analogous to those developed for autonomous vehicles in transport, are absent from all mining jurisdictions represented in the reviewed literature.

12. Limitations of the Review

Five limitations should inform the interpretation of the findings: (1) English-language bias, potentially underrepresenting significant operational DT deployments documented in Chinese, Russian, Spanish, or Portuguese literature; (2) temporal snapshot, as technology assessments, particularly regarding metaverse and foundation AI model integration, may be superseded within 12–18 months of publication; (3) publication bias toward positive results, biasing the evidence base toward reported successes; (4) quality assessment subjectivity, though inter-rater agreement reached $\kappa = 0.81$; and (5) industry data inaccessibility, as the most commercially significant DT deployments at large mining companies such as Rio Tinto, BHP, and Codelco are documented in grey literature and proprietary technical reports rather than peer-reviewed publications, limiting systematic assessment of the most advanced industry practice. A sixth limitation is geographic: as Fig. 4 shows, the corpus draws on only 22 countries, with 52.5% of studies originating in China and Russia and no representation at all from Sub-Saharan Africa, where large-scale open-pit gold, platinum, copper and cobalt mining is concentrated. Country attribution here follows first-author institution, which understates international collaboration but avoids double-counting. Taken together, these limitations suggest that the findings should be interpreted as indicative of current research trends rather than a complete representation of global DT deployment.

13. Conclusions

This systematic review of 120 publications provides the following principal conclusions: Of 120 included studies, 68 (56.7%) meet the minimum criteria for digital twins (L2–L4), while 52 (43.3%), initially labelled as such, were reclassified as digital shadows or digital models upon critical assessment. This systematic reclassification has direct implications for how adoption rates and field maturity are reported. Case-specific performance gains from operational DT deployments include a 44% output increase [18], 98.64% resource utilisation [47], a 21% EBITDA improvement [39], and a 40% risk management cost reduction in slope monitoring [40], all context-specific and not directly generalisable. The novel DT-M² Maturity Model and DT-AR Adoption Roadmap introduced here provide the first structured frameworks derived from a systematic review of the mining DT literature, offering practitioners and researchers a common vocabulary and evidence-based investment guidance.

Despite rapid advances, current DT systems in mining remain limited in their ability to represent subsurface geological variability reliably, cannot be deployed at new sites without extensive recalibration, cannot yet guarantee cybersecurity in adversarial environments [82], and cannot scale autonomously without large site-specific data investments [16]. These are current boundaries, not permanent ones, but they must be stated plainly. Safety management, the domain with the highest potential social impact, receives disproportionately less DT research investment than operational efficiency, and emergency rescue DT systems have not been validated in real accident scenarios [74]. These are urgent gaps.

The research-to-practice transfer gap is most severe in sub-Saharan Africa, Southeast Asia, and Latin America, which together account for a substantial share of global mineral production but contribute fewer than 5% of reviewed DT studies [2]. Targeted investment in DT research and deployment in these regions could deliver the greatest marginal safety and efficiency gains globally.

The central insight of this review is that despite rapid advances in digital twin technology for open-pit mining, current systems remain fundamentally limited by four interlocking constraints: insufficient geological data density for subsurface fidelity, the absence of standardised architectures preventing knowledge accumulation, unresolved cybersecurity vulnerabilities in safety-critical bidirectional systems, and a global workforce skill gap that outpaces technology deployment. Progress requires coordinated action across technology development, regulatory frameworks, industry standards, and workforce development, and the evidence base to guide that coordinated action is precisely what this review provides.

Author Contributions

Conceptualization, G.Y.B.; methodology, G.Y.B., J.S.L., N.Y.D.A. and K.B.; formal analysis, G.Y.B., J.S.L., N.Y.D.A. and K.B.; investigation, G.Y.B.; data curation, G.Y.B.; writing original draft preparation, G.Y.B.; writing review and editing, G.Y.B., J.S.L., N.Y.D.A. and K.B.; visualization, G.Y.B.; supervision, G.Y.B. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement

This study is a systematic review of published literature. No new datasets were generated or analysed. All data supporting reported results are contained within the cited publications.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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