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Review Article

Digital Twin-Enabled Monitoring for Deep Excavations in Mega Urban Developments

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Abstract: Deep excavations underpin transit-oriented districts, airport-linked complexes, high-rise mixed-use precincts, and underground utility corridors. In these dense settings, wall movements, ground loss, drawdown, and construction sequencing interact with vulnerable urban assets in ways that are difficult to observe and harder to predict. Digital twin technology is increasingly proposed as a response because it links field measurements with continuously updated virtual models for interpretation, forecasting, and intervention. This review synthesizes literature published between 2020 and 2025 on digital twins, geotechnical monitoring, deep excavation risk analytics, and urban digital infrastructure. Using a PRISMA-informed review design, the paper maps how sensing, BIM-GIS integration, physics-based simulation, machine learning, and uncertainty management are combined to support wall deflection control, settlement warning, groundwater management, and protection of adjacent buildings. The review argues that the value of a digital twin lies not in visualization alone but in the creation of a closed monitoring loop in which data, models, thresholds, and response rules are aligned to excavation stages and urban exposure. Two contributions are offered: a lifecycle architecture for twin-enabled excavation monitoring and a maturity-based implementation roadmap for mega urban developments. The synthesis shows that current advances are strongest in risk prediction, virtual sensing, and automated model updating, whereas major limitations remain in data interoperability, uncertainty communication, contractual governance, and scaling from pilot projects to district-level portfolios.

Keywords: Digital twin; deep excavation; geotechnical monitoring; mega urban development; risk management; urban underground construction.

INTRODUCTION

Deep excavations are now central enabling works for mega urban development's rather than peripheral geotechnical tasks. They make possible deep basements, transit interchanges, utility galleries, and cut-and-cover corridors in districts where land is scarce and underground space is heavily contested. These excavations are undertaken next to operating rail lines, busy roads, utilities, and occupied buildings, so performance must be monitored as an urban system rather than as an isolated retaining structure. Because wall deformation, ground settlement, pore-pressure change, and adjacent asset response evolve together, delayed interpretation can quickly convert manageable deviations into wider urban risk. Recent literature therefore treats excavation monitoring as an information integration problem as much as an

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instrumentation problem (Opoku *et al.,* 2021; Tan *et al.,* 2025). Digital twin research offers a useful response. In the built environment, a twin is increasingly defined as a data-connected virtual representation that exchanges information with the physical asset to support simulation, prediction, and decision-making (Lim *et al.,* 2020; Piras *et al.,* 2024; AlBalkhy *et al.,* 2024). Construction studies show growing use of twins for progress control, quality management, and resource coordination (Madubuike *et al.,* 2022; Baghdadi *et al.,* 2025). In geotechnical engineering, adoption is slower because subsurface conditions are heterogeneous, sensor coverage is incomplete, and high-fidelity numerical models are expensive to update during construction (Tan *et al.,* 2025). Yet these difficulties also make the approach attractive: excavation safety already depends on continuous comparison between expected and observed behavior, which is the central logic of a digital twin. The monitoring landscape is also changing. Conventional practice relied on periodic readings, threshold checks, and expert interpretation through static reports. That approach remains valuable, but it struggles when datasets are large, incomplete, and rapidly changing. Recent studies show that machine learning can improve prediction of settlement, wall displacement, and induced building risk, especially when spatial and temporal dependencies are modeled explicitly (Li *et al.,* 2023; Zhou *et al.,* 2024; Yang *et al.,* 2025a). Other work demonstrates that virtual sensing and imputation can estimate behavior at uninstrumented or faulty locations, extending monitoring beyond the installed sensor grid (Yang *et al.,* 2025b). These advances are most useful when embedded in a twin architecture that also contains geometry, staging logic, constitutive assumptions, and intervention rules. The literature remains fragmented, however. Some papers emphasize urban or built-environment digital twins without excavation specificity. Others focus narrowly on prediction models for adjacent buildings or settlement fields. Mega urban development's intensify these gaps because they contain multiple excavations, overlapping basements, long schedules, and shared receptors. A review focused specifically on digital-twin-enabled monitoring for deep excavations is therefore timely. The argument developed here is that a useful excavation twin is not a perfect mirror of the site but a selectively detailed, continuously updated system that turns heterogeneous observations into actionable urban risk intelligence. Mega urban developments also alter the temporal rhythm of monitoring. Excavation packages are frequently sequenced to protect program milestones for superstructure works, transport openings, or public-realm delivery, so the tolerance for delay is low even when uncertainty is high. This increases the temptation to treat monitoring as a compliance exercise rather than as a decision system. A digital twin is valuable precisely because it can resist that drift. By structuring data around exposure, stage, and response pathways, it allows monitoring to remain coupled to engineering judgment even under compressed delivery schedules.

Aim and Objectives of the Study

The aim of the study is to clarify how digital twins can improve monitoring, interpretation, and control of deep excavations delivered within mega urban developments. Four objectives guide the review: to identify the technological components used in twin-enabled monitoring; to evaluate how those components support geotechnical decisions during excavation; to synthesize recurrent implementation barriers in dense urban megaprojects; and to propose a maturity-based deployment roadmap and research agenda.

REVIEW METHODOLOGY

The review adopts a structured methodology informed by PRISMA 2020 guidance for transparent evidence synthesis (Page *et al.,* 2021). Because the topic crosses geotechnical engineering, construction informatics, and urban digital infrastructure, the search logic combined the terms "digital twin", "deep excavation", "foundation pit", "monitoring", "settlement prediction", "adjacent building", "BIM", "IoT", and "urban development". Searches were undertaken across Scopus, Web of Science, and ScienceDirect for the period January 2020 to December 2025, reflecting the recent acceleration of digital twin research in construction and geotechnics (Opoku *et al.,* 2022; Omrany *et al.,* 2025). Included publications addressed at least one of four themes: digital twin frameworks for construction or geotechnics; excavation monitoring systems connected to digital models; predictive analytics for excavation-induced response; and governance or interoperability issues relevant to urban implementation. Papers were excluded if they focused solely on structural digital twins without geotechnical interaction, on non-transferable sectoral twins, or on smart-city discussions with no excavation relevance. Preference was given to studies reporting prototype implementation, case validation, or clearly articulated monitoring workflows.

Analysis proceeded in three stages. Descriptive coding captured project context, response variable, data source, modeling approach, and stated output. Analytical coding then grouped the literature into six functional layers: urban context modeling, sensing and communications, state estimation, predictive analytics, decision support, and governance. Finally, cross-case comparison was used to examine where the literature converged and where it remained fragmented. This layered approach was chosen because excavation twins are assembled from interacting subsystems, not singular algorithms (Mousavi *et al.,* 2024; Cacciuttolo *et al.,* 2025). The result is a critical interpretive synthesis oriented toward practice, from which a conceptual architecture, maturity model, and implementation roadmap are derived.

Table 1: Review questions, scope, and synthesis protocol

Component	**Review focus**	**Application to deep excavations**
Primary question	How can digital twins improve monitoring and control from excavation start to basement closure?	Links sensing, modeling, prediction, and action to urban exposure.
Timeframe	2020–2025 peer-reviewed studies and applied framework papers.	Captures recent acceleration in construction and geotechnical twin research.
Evidence themes	Twin architecture; sensing and data fusion; predictive analytics; governance and scaling.	Ensures attention to both technical and organizational readiness.
Synthesis logic	Layered comparison across context, sensing, estimation, prediction, and intervention.	Translates fragmented literature into a transferable monitoring framework.

Digital twin architecture for deep excavations in mega urban developments

A digital twin for deep excavation monitoring should be conceived as a staged cyber-physical system rather than a single model. At minimum, it integrates five domains: the excavation and support system; the surrounding urban receptor field; the monitoring network; the numerical and data-driven models used to interpret behavior; and the decision environment in which interventions are authorized. Excavation-specific studies make this transition explicit. Wang *et al.,* (2024) proposed a data-mechanism-fused twin for smart risk management in deep excavation, where field measurements interact with a physics-informed model and a machine-learning prediction layer in a closed loop. Pan *et al.,* (2025) similarly developed a deep foundation pit twin that combines parameterized geometry, real-time updating, and visualization for whole-process risk control. These approaches move beyond "instrument, read, and report" by embedding monitoring inside a cycle of state estimation and risk forecasting. For mega urban developments, the architecture must begin outside the excavation footprint. The major consequence of excavation failure is often transmitted through the city: settlement affecting adjacent buildings, drawdown affecting utilities and pavements, or disruption to transport infrastructure. Urban digital twin studies therefore matter even when they are not excavation-specific, because they highlight the value of linking GIS, BIM, asset registries, and stakeholder dashboards to represent both the engineered object and its service environment (Piras *et al.,* 2024; Omrany *et al.,* 2025; Luo *et al.,* 2025). In excavation settings, wall deflection plots alone are inadequate; the twin must localize these responses against building foundations, road corridors, buried services, and neighboring construction packages. A second architectural layer is staging logic. Excavation risk changes with wall installation, bracing activation, excavation depth, slab casting, and dewatering transitions. A strong twin therefore requires a construction-state model that knows what stage the site is in, what behavior is acceptable for that stage, and what actions are available if observations deviate. This is where BIM-linked sequencing and schedule intelligence become valuable. Construction twin literature shows that linking progress, digital geometry, and time-dependent rules improves control and traceability (Madubuike *et al.,* 2022; Kang *et al.,* 2024). Applied to deep excavations, the same principle allows the twin to interpret whether wall movement reflects normal mobilization before strut prestress, or whether it indicates loss of restraint after support should already be active. A third layer is the model ecology. Numerical models are necessary for representing excavation mechanics, groundwater interaction, and the effects of support changes, yet they may be too slow or too uncertain to function as sole decision engines. Data-driven models react quickly to streaming measurements but may become unreliable outside the training domain. Recent studies respond through hybridization. Wang *et al.,* (2025) integrated uncertainty-informed deep learning into an excavation twin to improve prompt quantitative risk assessment. Li *et al.,* (2023) used explainable deep learning to predict excavation-induced building risk, while Zhou *et al.,* (2024) demonstrated that graph-based spatio-temporal learning captures settlement evolution more effectively than independent point models. The practical implication is that the twin should combine mechanistic plausibility with statistical adaptivity, and it should expose the uncertainty of both. The architecture must also preserve the logic of the observational method. Design assumptions should enter the twin as hypotheses to be checked against measured performance, not as immutable truths. Conversely, measured anomalies should not automatically be treated as evidence of failure. They need to be interpreted against construction sequence, support state, and uncertainty bounds. A good twin therefore acts as an organized conversation between design intent and field reality, making it easier to revise assumptions without losing traceability.

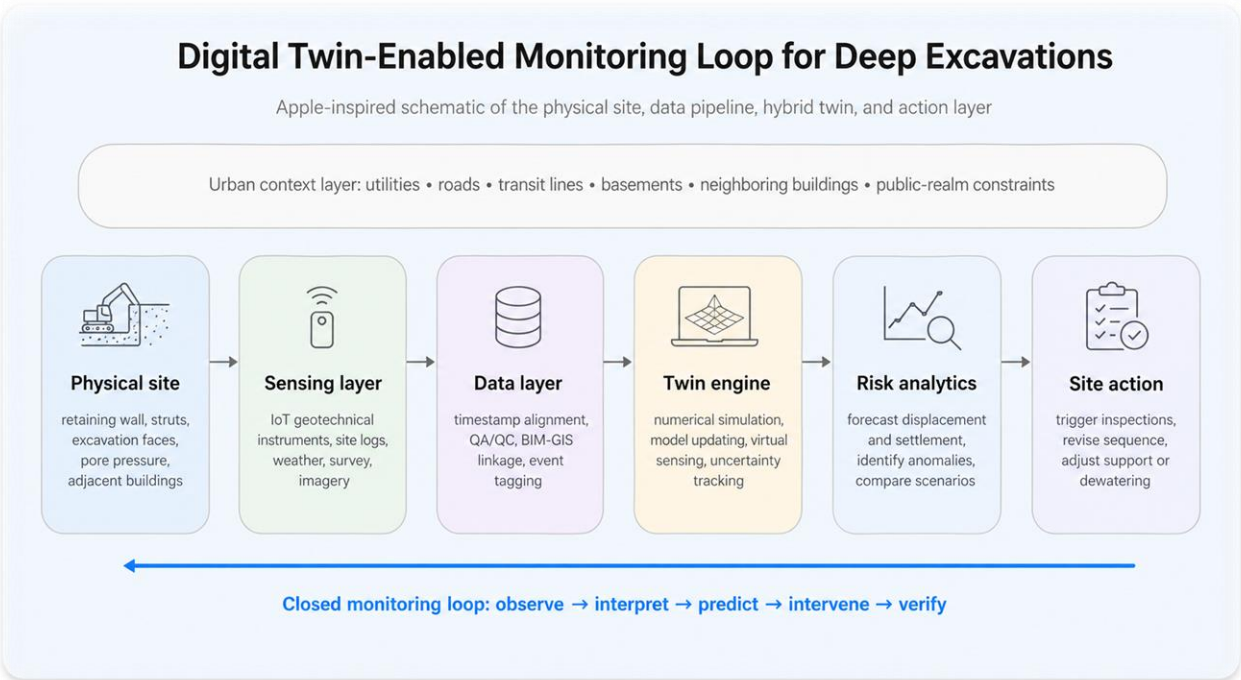

Figure 1: Closed-loop architecture for digital twin-enabled monitoring in deep excavations. The physical site, sensing layer, data layer, hybrid twin engine, risk analytics, and site action modules are arranged as an operational feedback loop suitable for dense urban megaprojects

Monitoring technologies, data fusion, and virtual sensing

The monitoring capacity of an excavation twin depends first on its sensing ecosystem. Conventional instruments remain the backbone of geotechnical observation: inclinometers, extensometers, settlement markers, piezometers, tilt meters, and strut load cells. Digital twin thinking does not replace them; it changes how their outputs are synchronized, interpreted, and supplemented. Reviews across the built environment emphasize that sensing, connectivity, and data semantics are core enablers of effective twins (Lim *et al.,* 2020; Piras *et al.,* 2024; Tan *et al.,* 2025). For deep excavations, this means that field instruments, construction logs, weather data, dewatering records, and nearby asset observations should be time-aligned and quality-tagged before advanced analytics begin. A major trend in the 2020–2025 literature is the shift from sparse readings toward multi-source monitoring. Yu *et al.,* (2024) showed how IoT integration and a digital twin environment can support large-foundation-pit safety analysis by bringing distributed monitoring into a coherent workflow. Cacciuttolo *et al.,* (2025) similarly demonstrated the value of multi-layer architectures in which sensing, preprocessing, storage, and analytics are separated but linked through explicit interfaces. In dense urban settings this is critical because excavation risk manifests across different media. A pore-pressure anomaly may precede settlement; traffic vibration may influence readings; utility leakage may distort dewatering interpretation. A twin that accepts only geotechnical instruments without site-production and environmental context will miss these couplings. Data fusion is therefore the central operational challenge. Fusion is not simply the collation of sensors on one dashboard. It requires synchronization across time steps, reconciliation of spatial reference systems, treatment of missing values, correction of drift, and classification of construction states. Several recent studies address this through advanced learning methods. Yang *et al.,* (2025a) introduced smart virtual sensing using real-time ensemble graph neural networks, showing that spatial structure can be exploited to estimate response at uninstrumented locations. Yang *et al.,* (2025b) then proposed graph recurrent neural network-based spatio-temporal imputation to improve reliability when excavation monitoring streams are incomplete. These approaches are particularly valuable in megaprojects, where access restrictions, staged handovers, and sensor damage can create persistent blind spots. A related theme is the movement from point prediction to field-aware interpretation. Settlement around excavations is spatially organized, and building response depends on both position and construction timing. Studies on adjacent building settlement prediction illustrate this well. Hu *et al.,* (2024) and Xu *et al.,* (2024) used foundation pit monitoring data to predict settlement induced by deep excavation, while Yin *et al.,* (2025) extended the logic to warning-oriented forecasting for surrounding buildings. For twin design, the implication is clear: monitoring data should be represented as spatial networks related to wall panels, strut bays, settlement zones, building footprints, and hydrogeological compartments, not as disconnected sensor streams. Dense urban projects further require explicit sensor prioritization. Not every variable can be monitored at equal density, so the twin should distinguish between leading indicators, confirmation indicators, and consequence indicators. Pore pressure and support force may act as leading indicators; wall displacement may serve as a confirmation indicator; settlement and building tilt may function as consequence indicators. This hierarchy helps project teams allocate scarce sensing resources while maintaining a coherent early-warning structure across the urban receptor field.

Analytics, model updating, and risk prediction

Digital twin value rises when monitoring data are translated into risk-relevant interpretation. In deep excavations, this analytical layer must support anomaly detection, short-horizon forecasting, causal interpretation, and intervention evaluation. Anomaly detection identifies behavior inconsistent with stage expectations or neighboring observations. Forecasting estimates likely future movement or risk under the current plan. Causal interpretation asks why the deviation is occurring. Intervention evaluation compares likely outcomes of changing the excavation sequence, support activation, or water-control regime. Risk prediction for adjacent buildings is now one of the most mature applications. Li *et al.,* (2023) developed a dynamic and explainable deep learning approach for excavation-induced risk on adjacent buildings, explicitly addressing interpretability through SHAP-based explanation. Ge *et al.,* (2025) addressed surface subsidence risk with an AI-driven architecture able to process multi-source monitoring data, while Lei *et al.,* (2024) used dynamic Bayesian reasoning and evidence theory to assess excavation risk in karst conditions. Together these studies suggest that a viable excavation twin should move beyond deterministic threshold alarms and represent risk as a dynamic, evidence-based quantity informed by both measurements and context. Model updating is the second critical function. An excavation twin cannot remain useful if its baseline model is frozen at design-stage assumptions. Soil stiffness, boundary conditions, dewatering effectiveness, and workmanship all evolve during implementation. Wang *et al.,* (2024) addressed this directly in their data-mechanism-fused excavation twin, where interactions between simulated and observed behavior support ongoing risk management. Wang *et al.,* (2025) extended the logic by introducing uncertainty-informed deep learning, thereby recognizing that timely risk estimation requires both updated predictions and explicit treatment of confidence. In mega urban developments, where interventions carry large schedule and contractual consequences, this distinction matters. If a twin predicts elevated settlement with poor confidence, the right response may be intensified monitoring and targeted investigation rather than immediate sequence interruption. A further frontier is the linking of excavation response to construction causality. Many monitoring systems forecast deformation while remaining agnostic about which site activities are driving the trend. Yet excavation management depends on causal hypotheses: new bench excavation, delayed strut prestress, local overbreak, rainfall, drawdown, or heavy construction traffic. Hybrid models that connect schedule events, site logs, and geotechnical measurements are still limited, but they are central to digital twin usefulness. Construction digital twin research shows that integrating progress data and operational states with asset models can improve traceability and managerial responsiveness (Madubuike *et al.,* 2022; Kang *et al.,* 2024). Applied to deep excavations, the same principle allows the twin to explain not only what is moving, but why. Threshold management also needs reinterpretation in a twin environment. Traditional amber-red systems assume that the significance of a threshold is stable through time, yet the same measured displacement can have different meanings before and after support activation, or under dry and wet conditions. A twin can improve this by defining thresholds as conditional and stage-dependent. In practice, that means warnings should be tied to both magnitude and trajectory, and should be assessed together with model confidence, construction state, and nearby receptor vulnerability.

Governance, implementation barriers, and mega-urban scaling

Mega urban developments are portfolio environments rather than single-project environments. Several excavation packages may operate simultaneously, sometimes with different support systems, different consultants, and different geotechnical baselines. Shared receptors such as metro tunnels, arterial roads, or district utilities may sit within the influence zone of more than one excavation. Under these conditions, the key implementation question is not simply whether a digital twin can be built, but whether it can coordinate information across organizational and spatial boundaries. Interoperability remains the first barrier. Reviews of construction and built-environment twins consistently identify fragmented data standards, weak semantic alignment, and poor integration between BIM, GIS, IoT, and analytics environments as recurrent obstacles (Opoku *et al.,* 2022; Piras *et al.,* 2024; Mousavi *et al.,* 2024). In deep excavations, these problems are acute because geotechnical observations are often stored in formats that do not align naturally with model-based construction platforms. Monitoring consultants may issue CSV files, contractors may manage site states in scheduling software, and designers may update numerical models offline. A true excavation twin requires these workflows to converge around shared identifiers, shared timing logic, and reliable version control. Governance is the second barrier. The literature frequently celebrates real-time monitoring and prediction, but less often addresses who has authority to act on the resulting warnings. In megaprojects, exceeding a threshold may require agreement among the excavation contractor, designer, checker, client, and public authority. If the governance chain is slow or ambiguous, the twin may detect risk earlier without enabling faster intervention. Digital twin deployment should therefore be linked to response protocols that specify thresholds, escalation routes, responsibilities, and documentation requirements. Descriptive twins visualize conditions. Predictive twins forecast likely behavior. But prescriptive twins also encode the organizational path by which model outputs are translated into action. A third barrier is economic and cognitive. High-resolution twins are expensive to maintain, and even well-funded projects may be unable to absorb the resulting information load. Site engineers need fast interpretation tied to immediate tasks; designers need calibrated response trends; clients need exposure summaries; authorities need receptor-focused warning logic. The most effective twin is therefore role-based and selective rather than encyclopedic. It does not display everything to everyone. The final barrier is scaling logic. A twin that works for one excavation may not scale to a district because computational demands, data heterogeneity, and stakeholder complexity grow nonlinearly. Portfolio implementation therefore requires a layered strategy: local twins for package-level control, federated district twins for shared receptor management, and city interfaces for coordination with public infrastructure. In mega urban developments, this federated model is more durable than the pursuit of one all-knowing urban twin. Human factors deserve equal attention. Even well-designed twins can fail if users do not understand what the visualizations mean, if alarm fatigue develops, or if teams come to trust automated outputs more than warranted. Training should therefore include not only software use but also the interpretation of uncertainty, the distinction between measured and inferred state, and the limits of predictive models under changing geology. In megaproject environments, the twin should support distributed expertise rather than centralize all authority in one control room.

Table 2: Maturity levels for twin-enabled monitoring of deep excavations

Level	Core capability	Typical output	Main management value
L1 Descriptive	Integrated dashboard of geometry, instruments, and stage records.	Visual trends and daily summaries.	Shared situational awareness.
L2 Diagnostic	Conditional thresholds linked to excavation stage and receptor class.	Alert lists and deviation explanations.	Faster triage and escalation.
L3 Predictive	Hybrid numerical and data-driven forecasting with uncertainty bands.	Short-horizon movement and risk forecasts.	Earlier intervention and more reliable planning.
L4 Prescriptive	Scenario comparison and authorized response workflows across packages.	Recommended actions, audit trails, and portfolio coordination.	District-scale risk control and traceable governance.

Deployment roadmap and maturity model

A practical maturity model for digital-twin-enabled excavation monitoring can be described in four levels. Level 1 is descriptive monitoring, where the twin consolidates geometry, instruments, and time-stamped dashboards but performs little automated interpretation. Level 2 is diagnostic monitoring, where deviations are linked to construction stages, thresholds, and historical trends. Level 3 is predictive monitoring, where hybrid physics-data models forecast settlement, wall movement, or adjacent asset risk over short horizons. Level 4 is prescriptive monitoring, where the twin compares intervention scenarios and supports authorized response protocols across the contractor–designer–client chain. Most documented systems currently sit between Levels 2 and 3. Pan *et al.,* (2025) and Wang *et al.,* (2024, 2025) approach Level 3, but sustained Level 4 deployment remains rare. For mega urban developments, progression through these levels should be staged rather than rushed. An effective roadmap begins with data governance and sensor quality assurance, because predictive capability cannot compensate for ambiguous or poor-quality inputs. The second stage links monitoring data to geometry, construction state, and receptor inventories through BIM-GIS integration. The third stage introduces calibrated predictive models and uncertainty displays focused on a small set of decision-critical variables. Only then should teams attempt automated intervention recommendation. This sequence reduces the common failure mode in which visually impressive twins are procured before the organizational and analytical foundations are stable.

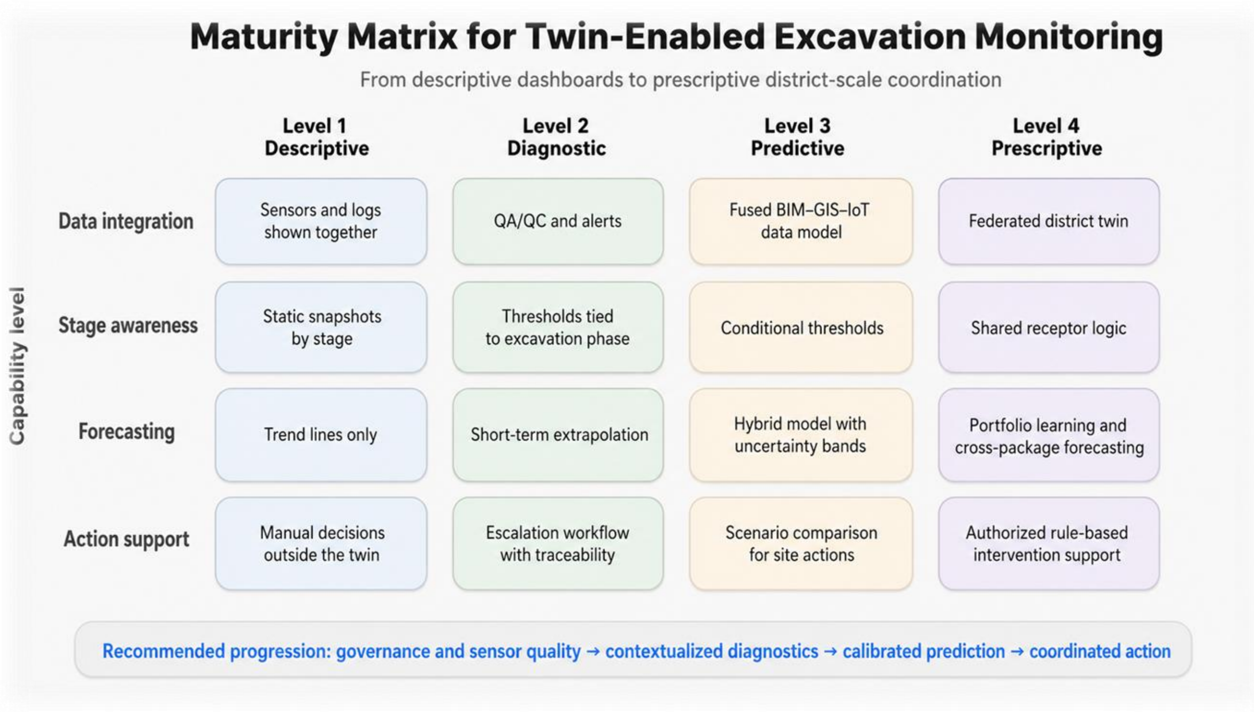

Figure 2: Maturity matrix for twin-enabled excavation monitoring. The matrix distinguishes descriptive, diagnostic, predictive, and prescriptive capabilities and links each level to progressively stronger monitoring, forecasting, and action-support functions

Future research directions

Five research directions appear especially important. The first is uncertainty-aware state estimation. Current studies increasingly recognize that monitoring intelligence must represent confidence, not just predictions. Work on uncertainty-informed deep learning for excavation twins is promising, but more progress is needed on probabilistic data assimilation, ensemble scenario analysis, and communication of uncertainty to field teams (Wang *et al.,* 2025; Tan *et al.,* 2025). The second is district-scale receptor modeling. Excavation twins still tend to focus on retaining walls, settlement points, or adjacent buildings in isolation. Future systems should model receptor networks that include utilities, pavements, tunnels, traffic corridors, and building clusters with different vulnerability classes. This would align excavation monitoring with broader urban digital twin research, which stresses cross-system interaction and resilience (Omrany *et al.,* 2025; Luo *et al.,* 2025).

Third, more work is needed on explainable hybrid modeling. Studies using SHAP and related tools have improved transparency, yet genuine acceptance will require models that express geotechnically meaningful factors and allow experts to challenge assumptions. This points toward tighter coupling between constitutive models, observational-method logic, and interpretable learning systems (Li *et al.,* 2023; Ge *et al.,* 2025).

Fourth, implementation research must catch up with algorithmic innovation. There is still limited evidence on procurement models, contractual allocation of responsibility, cybersecurity practice, and long-term information stewardship for excavation twins. Comparative case research across megaprojects would be especially valuable because different governance arrangements may explain twin performance as much as technical design.

Fifth, future twins should support learning across projects without erasing local specificity. A promising path is federated knowledge architecture, in which anonymized features, event types, and performance signatures are shared across excavation portfolios while sensitive project data remain local. Such an approach could improve model robustness, accelerate warning-rule development, and help city authorities learn from repeated excavation patterns.

A final research priority concerns benchmark datasets and evaluation protocols. Many current studies are project-specific, use different variables, and report performance in inconsistent ways, which makes cross-project learning difficult. Shared benchmarks for wall movement, settlement, pore pressure, support force, and building response would help the field compare models more rigorously and identify where hybrid twins genuinely outperform traditional monitoring practice. Without such benchmark culture, the field risks accumulating impressive but non-comparable demonstrations.

CONCLUSION

Digital-twin-enabled monitoring offers a credible path toward better control of deep excavations in mega urban developments because it connects sensing, interpretation, and intervention within one evolving decision environment. Literature from 2020 to 2025 shows clear progress in excavation-specific twin architectures, predictive analytics for adjacent assets, virtual sensing, and uncertainty-aware risk estimation. At the same time, the review demonstrates that technology alone does not guarantee safer excavations. Twin effectiveness depends on the quality of monitoring inputs, the staged linking of models to construction reality, and the governance arrangements that allow warnings to be converted into action. The central conclusion is that the most useful excavation twin is neither a static 3D model nor a generic smart-city dashboard. It is a staged, role-based, and uncertainty-aware system designed around the observational method and urban receptor protection. In mega urban developments, such twins should be implemented through federated architectures that preserve package-level detail while enabling district-wide coordination. When built on that basis, digital twins can improve risk transparency, decision traceability, and intervention timing, helping underground urban growth proceed with greater technical discipline and public confidence. Their long-term significance will depend on disciplined calibration, transparent uncertainty reporting, and consistent linkage between model outputs, construction decisions, and documented urban safeguards across the full excavation and basement delivery cycle in practice.

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