

Digital twins for urban underground space

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19 **ABSTRACT**

20 *Digital twins (DTs) offer promising benefits to address several inherent problems in*
21 *underground construction, yet confusion surrounds the concept due to its context-specific*
22 *nature which hinders more widespread adoption. This paper seeks to clarify DT-related*
23 *terminologies from a built environment perspective and define the features and maturity levels*
24 *of DTs for underground spaces, considering their unique challenges. A layered architecture*
25 *for constructing DTs is proposed, offering various options based on functionality,*
26 *technological advancement, and expected value. Additionally, a comprehensive literature*
27 *review of technologies enabling the development of digital twins for underground spaces is*
28 *presented, including data-driven ground modelling, site investigation and design process*
29 *integration with BIM, computational BIM, and advanced sensing and instrumentation. The*
30 *paper identifies synergies between DTs and the observational method in geotechnical*
31 *engineering, highlights research gaps, and proposes a transition to a prescriptive, knowledge-*
32 *based DT. Furthermore, exemplar use cases of underground DTs throughout their lifecycle are*
33 *explored, demonstrating their potential value.*

34 *Keywords: BIM, digital twins, observational method, underground construction.*

35 **1 INTRODUCTION**

36 Escalating demand for infrastructure, including housing, energy, water, sanitation, and
37 transport, combined with above-ground congestion has propelled recent significant increases
38 in underground construction. For instance, 10% of our rail network in Europe is located
39 underground, and in London, this figure rises to 45% (*Pritchard and Preston 2018*). However,
40 traditional underground construction methods struggle to meet the rising demand due to issues
41 such as low productivity, prolonged construction timelines, high costs, and safety concerns
42 (*Quigley et al. 2016; Sun et al. 2023*). Uncertainties in ground conditions and various design
43 and construction stages exacerbate these challenges.

44 Digital technologies emerge as one of the promising enablers to overcome these limitations
45 and revolutionise underground construction by offering unprecedented capabilities in planning,
46 monitoring, and execution. The adoption of building information modelling (BIM) has
47 improved delivery and performance, fostered collaboration and innovation, and introduced
48 opportunities for a new level of automation. Although widely used in the construction industry,
49 the current adoption level and capabilities of BIM does not fully exploit the full range of
50 benefits of the digital revolution. Digital twin (DT) is an emerging solution within the industry

51 4.0 framework, which was first proposed as a conceptual model for product lifecycle
52 management by *Grieves (2002)*. It refers to a set of virtual information representations that
53 mimics the structure, context, and behaviour of a natural, engineered, or social system which
54 is dynamically updated with data from its physical counterpart and has a predictive capability
55 to inform decisions for realising value (*AIAA 2020*). It offers real-time monitoring,
56 performance analysis, and predictive maintenance, contributing to enhanced productivity,
57 safety, and operational efficiency (*Amthiou et al. 2023*).

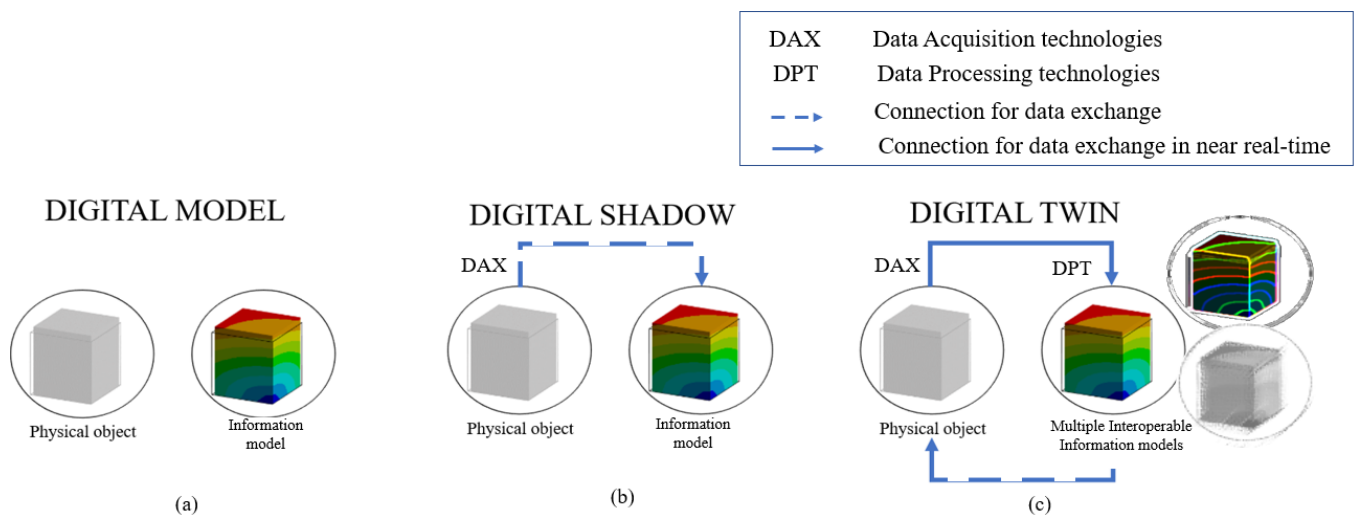
58 The term DT has become commonplace jargon due to its expansive applicability across various
59 industries and contexts particularly in the fields of manufacturing, production, and operations
60 (*Camposano et al. 2021*). There can be different scales of DTs ranging from physical products
61 (objects/ components), system or processes. Accordingly the contemporary digital
62 representation may capture physical entities such as aircraft engines, social constructs and
63 processes such as stock market operation, and composite systems which encompass both of
64 these, such as construction projects (*Kritzinger et al. 2018*). The basic premise of DTs is to
65 solve information silo problems by combining and linking isolated data or models in different
66 field spaces, time domains and cognitive contexts of complex systems (*Hu et al. 2023*).

67 Due to the broad applicability of DTs, different organisations define and interpret DT concepts
68 based on domain-specific functions and characteristics (*Kritzinger et al. 2018*). These different
69 interpretations have led to significant confusion and misunderstandings associated with DTs.
70 *Tao et al. (2019a)* state that a DT has three main elements: a physical artefact, a digital
71 counterpart that mirrors the physical artefact, and the connection that binds the two. It has also
72 been proposed that a true DT should provide a service, such as simulation, monitoring and
73 decision-making, and/or control of the physical object (*Tao et al. 2019b*). In construction, DTs
74 are commonly misinterpreted as digital models of assets (e.g., only 3D BIM models) or as
75 simulations for prediction of behaviour. However, DTs go beyond these as they are virtual
76 replicas of real-world physical products or systems (*Naderi and Shojaei 2023*).

77 In the realm of digital representations, the connection between elements differentiates a DT
78 from related concepts such as a digital model and a digital shadow, each serving distinct
79 purposes (see Figure 1). A DT incorporates a bidirectional and near real-time exchange of data,
80 information, and knowledge between the physical and virtual counterparts, enabled by data
81 acquisition technologies (DAX) like advanced sensing, internet of things (IoT), high-speed
82 networking, and machine learning (ML) and data science technologies (data processing

83 technologies) (Sacks *et al.* 2020a), which may even have a human in-the-loop to make
 84 decisions (Agrawal *et al.* 2023; Zhang *et al.* 2022). DTs can also involve multiple interoperable
 85 information models such as geometric model, analytical model, behavioural models to create
 86 living transdisciplinary simulations that update and change in real-time in response to changes
 87 of the physical counterpart over the whole lifecycle. Such information models can then be
 88 employed for optimising processes, supporting decision making, virtual control, and analysis.

89 A digital model, on the other hand, is a static, often only a geometric representation of an object
 90 or system. It supplies a simplified, non-real-time view for design, visualisation, and analysis.
 91 Lastly, a digital shadow refers to a digital representation encompassing historical data and
 92 behaviours, offering insights into past performance and aiding in predictive analytics but
 93 missing near-real time data processing, interoperability between different information models
 94 and feedback to the physical twin (Fuller *et al.* 2020).



95 (a) (b) (c)

96 *Figure 1: Conceptual representation of (a) digital model, (b) digital shadow, and (c) digital twin*

97 This paper identifies the challenges in developing DT for underground space and presents a
 98 conceptual definition and maturity levels of underground DTs. Further, research in
 99 technologies which will be future enablers for underground DT has also been recognised. A
 100 key academic contribution of this paper is a vision for transitioning from a well-developed and
 101 codified observational method in geotechnical engineering to knowledge-based prescriptive
 102 DT. Further, this study demonstrates value delivered by underground DT throughout the
 103 lifecycle by providing exemplar use cases.

104 **2 DIGITAL TWINS IN CONSTRUCTION INDUSTRY**

105 While DT technology has gained attention in various sectors, its application in construction is
106 still in its infancy (Wu et al. 2022a). The Centre for Digital Built Britain (CDBB) defines DTs
107 as “a realistic digital representation of assets, processes or systems in the built or natural
108 environment” (Bolton et al. 2018). Boje et al. (2020) notes that a comprehensive definition of
109 a DT should delineate both its ontological dimensions detailing its inherent properties, and its
110 epistemological aspects, explaining the methods and processes through which knowledge
111 about the DT is acquired and validated. It should be purpose driven and should identify the
112 fundamental information and technology elements, clarify the interconnections among these
113 elements, and discern their individual and collective functionalities.

114 Jiang et al. (2021) interpreted a construction DT to comprise five parts: (i) the physical
115 components/ systems, (ii) the digital representation, (iii) physical-digital connections, (iv) data
116 and (v) service. Figure 2 describes the various mandatory and optional components required
117 for a construction DT according to Jiang et al. (2021). More recent frameworks like Torzoni
118 et al. (2024) define predictive capabilities as being a core requirement for civil engineering
119 applications; these are considered as offerings of the service component of DT framework as
120 shown in the Figure 2.



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122

123 *Figure 2: Essential and optional connections of DT according to Jiang et al. (2021)*

124 There has been a marked increase in DT research applied to construction since 2018, with
125 scholars exploring various phases of the construction lifecycle. In the engineering and design

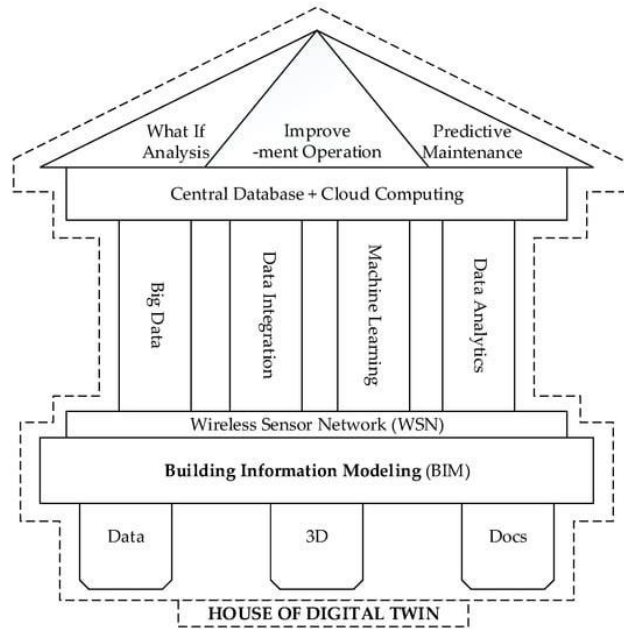
126 phase, the focus has been on structural and layout optimisation, quality assessment and
127 improvement in design management by optimising information flows to enhance productivity
128 by reducing design time and rework costs (*Moshood et al. 2024; Opoku et al. 2021*). BIM is
129 considered a cornerstone for creating a DT for collaborative information-sharing and decision-
130 making regarding material selection, energy management (*Kaewunruen and Lian 2019*) and
131 procurement. However, some researchers consider these as secondary applications of DT, as
132 they are fundamentally aligned with the virtual design and construction (VDC) concepts which
133 was first introduced in 2001 as part of the by the Centre for Integrated Facility Engineering at
134 Stanford University (*Rafsanjani and Nabizadeh 2023*).

135 For the construction phase, previous research has primarily centred on assessing the integrity
136 of structural systems e.g. *Angjeliu et al. (2020), Gerhard et al. (2020)*. Additional research has
137 considered construction progress, budgeting, value, quality, sustainability and carbon footprint
138 assessment (*Huang et al. 2023a*), and safety monitoring and management (*Jiang et al. 2021;*
139 *Teizer et al. 2022*). DTs have been most widely applied to the operation and maintenance phase,
140 particularly for facilities management, involving advanced building management systems for
141 optimising energy use and structural health monitoring of buildings (*Kaewunruen and Lian*
142 *2019*). However, there is a notable lack of literature related to the application of DT to the end-
143 of-life/demolition phase (*Opoku et al. 2021*).

144 The digital twin consortium, which is a global organisation that works to develop digital twin
145 technology, highlights the required capabilities of a DT in six key categories - data services,
146 integration, intelligence, user experience, management, and trustworthiness (*McKee 2023*).
147 The Gemini principles provided by CDBB advocates the requirement of similar principles.
148 These principles, range from ensuring a clear purpose and public good to prioritise data security
149 and openness to emphasising the importance of establishing reliable and functional DTs.
150 Federation is identified as a key element i.e., the linking of multiple DTs from different sources
151 or organisations to create a more comprehensive and interconnected network.

152 The construction of a DT requires the integration of various enabling technologies. *Khajavi et*
153 *al. (2019)* proposed the “House of DT” framework (Figure 3) to identify such technologies. It
154 is crucial for the model to hold both graphical and semantic information, which is possible with
155 BIM. IoT and sensor technologies capture real-time data from the object or structure of interest.
156 These data streams are then analysed using data analytics and ML to derive meaningful
157 insights. Visual programming extends BIM models, allowing computations and connections

158 with the sensor network. Cloud-based servers often serve as databases for storing extensive
 159 data and virtual models. The advancements in BIM, including increased interoperability, data
 160 accuracy, collaboration abilities, and enhanced visualisation and simulation capabilities,
 161 contribute to the development of DT from BIM (Nguyen and Adhikari 2023).



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163 *Figure 3: House of digital twins defined by Khajavi et al. (2019)*

164 **3 UNDERGROUND DIGITAL TWINS**

165 **3.1 Challenges in underground space**

166 Within the specialised domain of underground space, DT research is still regarded as “new
 167 territory” (Wu et al. 2022a). Given the domain specificity of DT definition and maturity levels,
 168 underground construction requires a specialised approach to DT concepts due to the unique
 169 challenges associated with subterranean environments. For example, subsurface conditions are
 170 inherently uncertain, non-uniform and anisotropic. The intricate relationship between the
 171 ground and structure introduces complexity through non-linear and temporally varying
 172 parameters, distinguishing it from conventional structural analysis for system identification.
 173 This necessitates a denser and more continuous network of sensors to collect data. The acquired
 174 data are also often multivariate, uncertain, sparse, incomplete, and potentially corrupted with
 175 spatial/temporal dimensions, which adds complexity to follow-on analysis (Phoon et al.
 176 2022a). Geological data introduces a three-dimensional (3D) variation that poses measurement
 177 challenges not encountered in above-surface infrastructure. Moreover, the sensors required for
 178 underground construction are usually buried, or embedded within structures which are difficult

179 to access, necessitating the use of sensors with high durability and low signal interference from
180 various dynamic factors such as settlements, water seepages and chemical exposure.

181 Data management also faces unique issues of format standardisation - for instance industry
182 foundation classes (IFC) and CityGML are not finalised due to the complexity of geological
183 data and structure interaction, differences of excavation methods and supporting strategies
184 (*Huang et al. 2021*). The distinctive characteristics of geological objects require the
185 simultaneous maintenance of multiple solid representation schemes. These issues have also led
186 to a lagged implementation of BIM in underground space compared to above-ground
187 structures. However, the upcoming IFC version aims to address some of these challenges (*Rives*
188 *et al. 2020*).

189 Unlike DTs for surface structures, the numerical modelling, 3D geological visualisation,
190 mapping of surrounding utilities in the subsurface itself involves the application of
191 sophisticated sensing/ exploratory methods, complex simulations, data, and analytics. These
192 complexities, including a multi-disciplinary nature, a high degree of customisation, and long-
193 term cycles of underground infrastructure, call for a unique paradigm of DTs for underground
194 space (*Li et al. 2024b*), requiring separate maturity levels, and further research and exploration.

195 **3.2 Maturity dimensions of underground DT**

196 The maturity levels of DTs indicate their development stages within a sector, facilitating the
197 definition, management, and integration of their progress. Researchers have assessed maturity
198 based on factors like information flow (*Fuller et al. 2020*), technological advancement, and
199 functionality by include aspects like model, data, content, level of control, human-machine
200 interaction, and computing capability (*Uhlenkamp et al. 2022*). DTs cover a broad spectrum of
201 dimensions, including functional completeness, federation, and value, rather than merely being
202 a technological overlay or following a linear progression. Based on these factors the maturity
203 model for the construction industry can consists of four dimensions: descriptive twin, reflective
204 twin, predictive twin, and prescriptive twin as defined in the Table 1 along with the description
205 of each dimension. Further *Li et al. (2024)* proposed several rubrics for evaluating these
206 dimensions in the context of underground space, and the degree of development is graded as
207 different levels of maturity, as summarised in Table 2.

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Table 1: Dimension of DT maturity pertaining to construction

Maturity dimensions	Description	Key Questions Addressed
Descriptive Twin	Collects geometric, material, performance, and historical data to recreate entities digitally. Lacks real-time updates and analysis (<i>Gürdür Broo et al. 2022; Sacks et al. 2020a</i>)	“What is it?”
Reflective Twin	Uses sensors and instant communication for real-time status updates, visualising construction progress, operations, and structural responses. Promotes efficient decision-making with sensing and control (<i>Agrawal et al. 2023</i>)	“What is happening?”
Predictive Twin	Predicts future states like mechanical responses and risks using statistical, mechanistic, and knowledge models. Continuously optimises with field feedback (<i>Torzoni et al. 2024</i>)	“Why is it happening?” and “What will happen?”
Prescriptive Twin	Analyses and optimises construction and operations, providing real-time decisions. Supports remote and automated control of intelligent devices (<i>Wang et al. 2021</i>).	“What should be done?”

212 *Table 2: Summary of rubric grading for DT maturity evaluation in underground infrastructure (Li et*
 213 *al. 2024b)*

Dimension	Maturity Rubric	Level-1	Level-5
Descriptive twin	Data & semantic richness	Single-scale, multiple components, basic data	→ Multi-scale, multiple components, linked data structures
	Model quality	Actual data, low (level of detail) LOD, low fidelity model with acceptable error	→ Actual data, real-time, multi-LOD models
	Model completeness	Geometric (OR) process	→ Geometric (AND) behavioural (AND) process
Reflective twin	Sensing capabilities	Manual, partial sensing	→ Autonomous sensing
	Interoperability	Data & model partially standardised and federated	→ Fully standardised, highly federated, and high-security sharing
	Connection capabilities	High manual intervention, low fidelity	→ Integrated and automated connectivity and high fidelity
	Model update capabilities	Partially updatable attributes, delayed update	→ Fully updatable attributes, real-time updates
Prediction twin	Analysis capabilities	Actual data supported, manually constructed analysis.	→ Multi-physics and automatic analysis model enhanced by feedback
	Prediction capabilities	Data-driven fitting prediction	→ Scenario deduction for complex systems
Prescriptive twin	Decision capabilities	Artificial control, parametric design enabled	→ Feedback-optimised autonomous control, generative design based

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 215 *Note: If the rubric does not meet the requirements of Level 1, the level should be 0 and not*
 216 *qualified as DTs.*

217 Accordingly, the concept of underground DT is not confined to a rigid definition; it
 218 encompasses a spectrum of possibilities and variations. Each dimension of a DT can have
 219 different levels of advancement based on the context of application. The degree of
 220 advancement depends on the specific use case and the expected value from adopting a DT
 221 approach, as outlined in the rubrics in the table.

222 3.3 Construction of an underground DT

223 The underground DT should capture both the physical entities and the processes involved for
224 design, construction, operation, and end-of life phases of underground structures. Figure 4
225 conceptualises a layered architecture for an underground DT. This architecture begins with a
226 physical layer, that encapsulates entities and processes integral to underground construction
227 such as: (i) site environment capturing the geophysics, hydrology, geology, and topography of
228 the site, (ii) foundation structures - including various components such as piles, rafts and
229 retaining wall, (iii) temporary support structures- such as struts and walers, anchorages, tie rods
230 and shotcrete, (iv) dewatering arrangements and, (v) utilities and services. The data richness,
231 model quality, and completeness of these entities can vary depending on the context and use-
232 case.

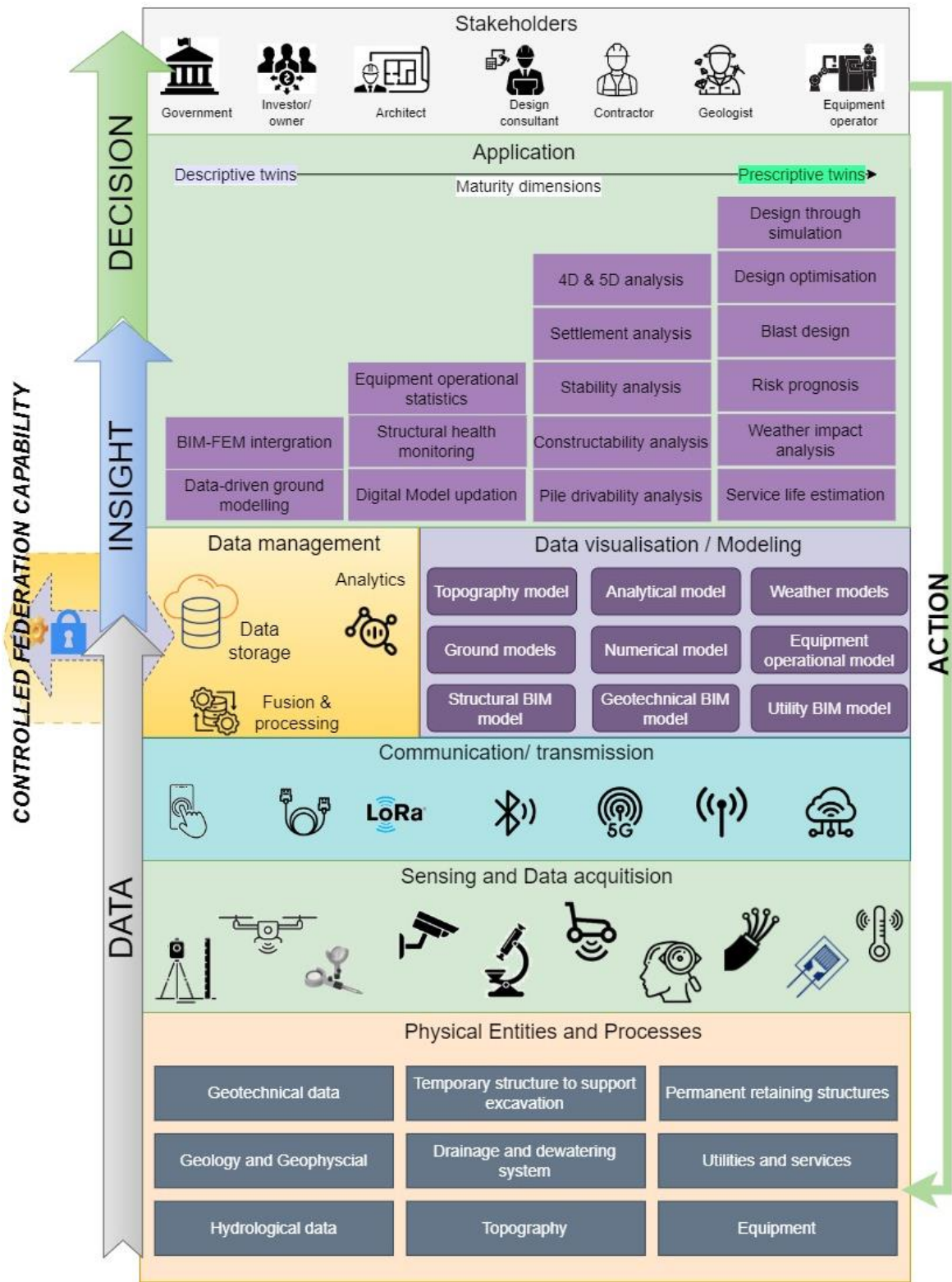
233 Data from the physical layer is captured by the sensing and data acquisition layer, which utilises
234 various sensing equipment. This equipment ranges from survey data and laboratory test for
235 various geological and engineering parameters to satellite imagery, strain sensors,
236 inclinometers, piezometer, geophysical equipment (e.g., ground penetration radars (GPR)), and
237 vision data (computer and/or human). The maturity of the underground DT depends on the
238 degree of automation in sensing and the reliability and accuracy of the data collected. These
239 data are then transmitted to the data management layer by the transmission layer. Depending
240 on the data type, range of data transfer, and connection requirements, the transmission layer
241 can employ a broad spectrum of methods, from wired connections to high-fidelity wireless
242 connections. IoT-enabled sensing and advancements in edge computing can also integrate the
243 sensing, transmission, and data management layers to a high degree.

244 In the data management layer, collected data are stored and processed. This layer is capable of
245 fusing and processing data from multiple sources, performing preliminary analytics, and
246 storing data in databases. It should seamlessly interface with the visualisation and modelling
247 layers, where BIM plays a pivotal role. Additionally, the data management layer enables data
248 exchange with various software packages or plugins used in the application layer. Leveraging
249 these inputs, a virtual model is created using a multi-physics approach to depict various details
250 of the subsurface environments. This model encompasses diverse semantic information and
251 reflects engineering properties, serving as the foundation throughout the structure's lifecycle.
252 Dynamic display features of the DT simulate real-time state changes, enabling the prediction
253 of potential states in actual underground construction (*Wu et al. 2022a*).

254 The application layer of the underground DT provides a range of solutions and simulations,
255 from descriptive twin applications to more advanced prescriptive phases. Example solutions
256 include data-driven ground modelling, real-time model updating, structural health monitoring
257 and warning systems, and automated analyses such as settlement, stability, and constructability
258 assessments. It also includes risk prognosis, design, cost, and carbon optimisation simulations.
259 Stakeholders use this layer to make real-time decisions based on multi-scale federated views
260 of the entities and processes in the physical layer. The decision-making and decision
261 implementation may also be automated in some applications, such as in the concept of
262 hypertunnel, where swarm robotics is used for tunnelling works autonomously informed by the
263 prescriptive digital twin (*King 2022*).

264 The data management layer plays a central role in the proposed architecture, where all the data
265 are stored. Figure 5 which is a high-level abstraction of figure 4, illustrates the interaction
266 between various layers within an underground DT and other DTs. The data storage, in a
267 common data environment, should be seamlessly accessed and modified by the data
268 visualisation and modelling layer, where BIM is pivotal. The data management layer must also
269 support data exchange with various software packages or plugins in the application layer.
270 Stakeholders can always access the data management layer to view raw or semi-processed data,
271 the visualisation layer to view and edit BIM models, and the application layer to run
272 simulations or analyses on the BIM models based on data from the data management layer.

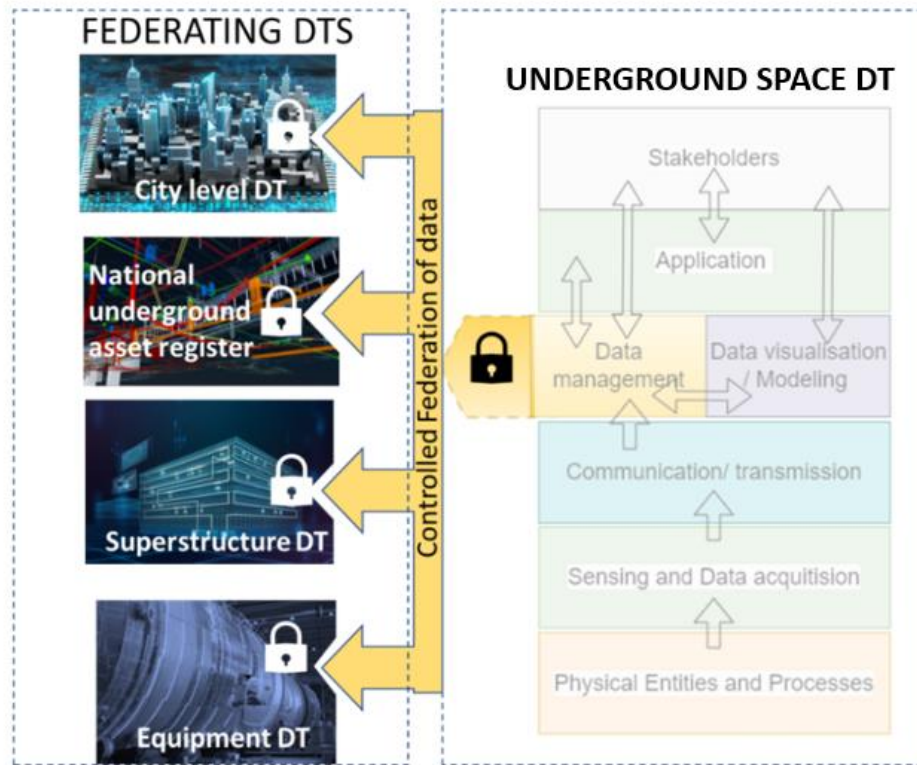
273 The architecture also includes a controlled federation with secured two-way data exchange
274 capabilities with other DTs, such as the city level DT (an ecosystem of DTs connected via
275 securely shared data; *Bolton et al. 2018*), superstructure DT, equipment DTs etc., aligned with
276 the Gemini principles for DT development. The “*National Underground Asset Register*
277 (*NUAR*)” (2024) is a project which is developing a basic DT which integrates data of various
278 underground assets in the UK. Federation of the underground DT with these DTs will be
279 crucial. Similar project has also been undertaken in Singapore (“*Singapore-ETH Centre*”
280 2023). Federation is not limited to these external DTs, but each component in the physical layer
281 can have its own DT (e.g., equipment DTs), contributing to the formation of the underground
282 DT (see Figure 4). While federation is desirable for DT development (*Huang et al. 2023c*), the
283 computational complexity and cost associated with exchanging data across all federated DTs
284 may be challenging for a universally applicable DT (*Li et al., 2024*).



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Figure 4: A conceptualisation of an underground digital twin architecture



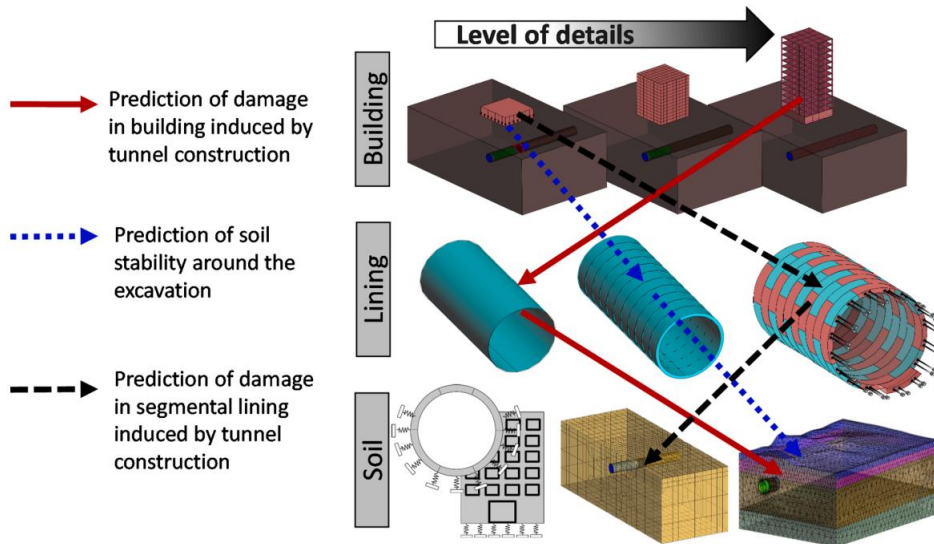
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288 *Figure 5: Interaction between different layers within underground DT and federation across DTs*

289 To address this challenge, a trade-off between fidelity and computational efficiency must be
 290 considered. A recommended approach is to adopt a multi- LOD model of appropriate
 291 abstraction level of and technology, aligned with specific scenarios and purpose for data
 292 federation. The resulting multi-scale modelling and multi-level LOD representation approach
 293 will provide model precision according to the need of a particular application whilst
 294 simplifying representations for other applications. Figure 6 illustrates an example, where *Ninić*
 295 *et al. (2020)* has adopted this multi-LOD approach to establish efficient data exchange between
 296 various models to suit analysis requirements of different stakeholders.

297 One of the primary functions of the data management layers is data fusion and processing. The
 298 key challenge lies in handling heterogeneous data from different sensors, along with temporal
 299 and spatial misalignments, and complex models due to the multi-physics nature of underground
 300 spaces. Probabilistic fusion models, such as Bayesian networks, are effective in environments
 301 with inherent uncertainty, combining data with varying confidence levels to predict outcomes
 302 or assess risks (*Macías et al. 2024*). Semantic data fusion becomes essential when the meaning
 303 and context behind data are critical (*Li et al. 2024c*). Ontologies and knowledge graphs enable
 304 the integration of heterogeneous data by providing a formal structure for defining concepts,
 305 relationships, and rules within a domain. This ensures consistent interpretation and allows for

306 advanced querying and inference, leading to more accurate and context-aware decisions, which
 307 are vital for developing digital twins in complex infrastructures like underground spaces (*Yu et*
 308 *al. 2021*).



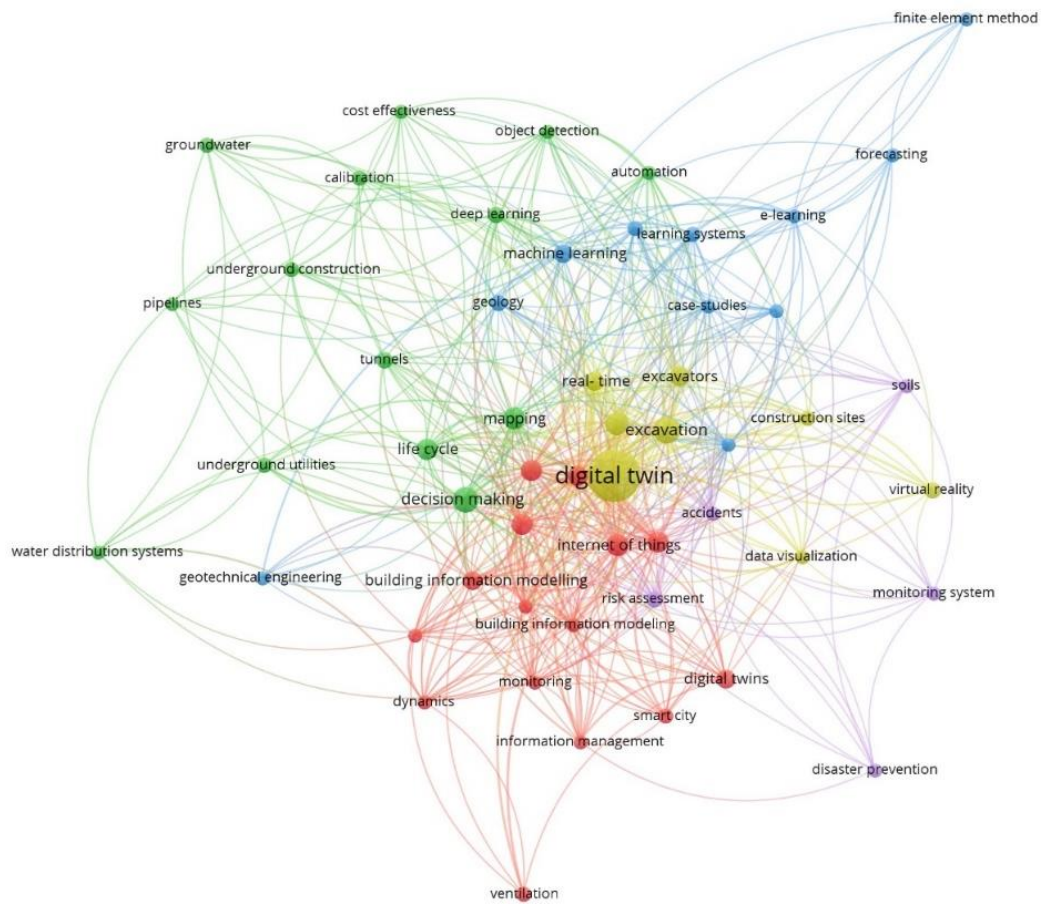
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310 *Figure 6: Example of a multi-LOD approach for federation of DTs (reproduced from (Ninić et al.*
 311 *2020b))*

312 **4 IDENTIFYING KEY RESEARCH AREAS INFLUENCING THE** 313 **DEVELOPMENT OF UNDERGROUND DTS**

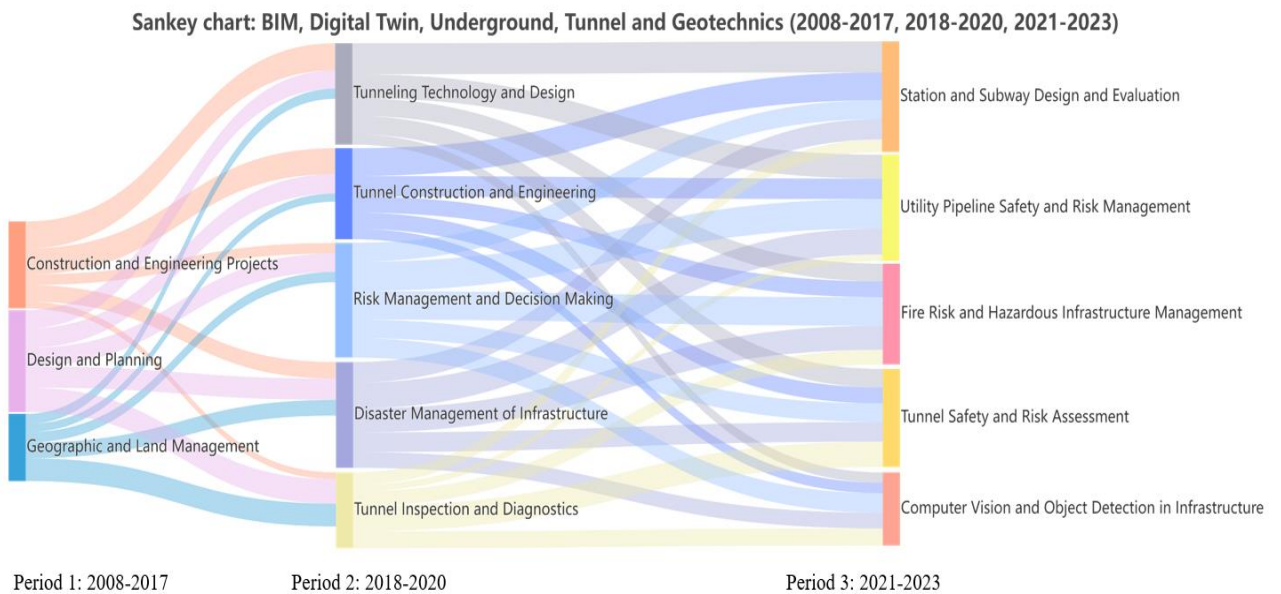
314 Underground DT literature is highly fragmented, with applications ranging from tunnelling
 315 operations to risk prognosis during deep excavations. Figure 7 presents a keyword co-
 316 occurrence map based on a comprehensive concatenated Scopus search incorporating DT and
 317 underground construction which provides insights into the prevailing research landscape. This
 318 visual representation serves as a valuable guide in recognising the focal points of underground
 319 DT research which feature BIM, the finite element method (FEM), ML, sensing, and
 320 monitoring systems as prominent areas.

321 Figure 8 presents a Sankey diagram constructed using Latent Dirichlet Allocation-based topic
 322 modelling of the titles and abstracts from a Scopus database search with the keywords ‘BIM’,
 323 ‘digital twin’, ‘underground’, ‘tunnels’, and ‘geotechnics’, to understand the evolution of
 324 research topics in this area. Design evaluation, risk assessment, and the application of computer
 325 vision for sensing feature as emergent areas.



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Figure 7: Mapping of co-occurrence of keywords (based on 275 select papers; minimum number of occurrence was set to 4; search criteria (TITLE-ABS-KEY (underground OR excavation OR geotech*) AND TITLE-ABS-KEY (digital AND twin OR bim)) AND (LIMIT-TO (SUBJAREA , "ENGI")) OR LIMIT-TO (SUBJAREA , "COMP"))



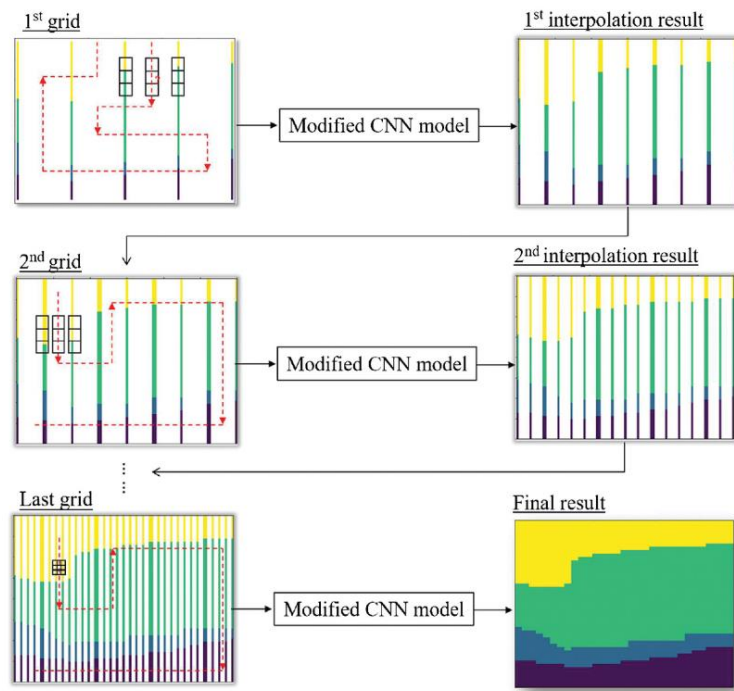
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Period 1: 2008-2017 Period 2: 2018-2020 Period 3: 2021-2023
Figure 8: Evolution of research topics in BIM and DT pertaining to underground, tunnels and geotechnics- adopted from Ninić (2024)

335 A comprehensive literature review is described below to identify priority technical challenges
336 and ongoing research areas for underground DTs, informed by Figure 7 & 8. These challenges
337 include BIM integration with site investigation data, BIM-based ground modelling methods,
338 BIM-FEM interoperability, and advanced sensing, instrumentation, and monitoring. Another
339 area of active research in construction is computational BIM which can significantly influence
340 the development of underground DTs. A proactive understanding of these advancements is
341 essential for the development of a well-integrated underground DT.

342 **4.1 Data-driven ground modelling**

343 Ground models are a digitised model characterising each sub-surface element with parameters
344 that define the ground behaviour, such as layer thickness, geo-structural features, and
345 mechanical/hydraulic properties. Obtaining a precise site representation from limited disparate
346 data is challenging. Interpolation methods are broadly categorised as deterministic (e.g.,
347 splines, inverse distance weighting, polynomial interpolation) and probabilistic (e.g., kriging,
348 sequential simulation). Deterministic methods are convenient but overlook natural ground
349 variability and uncertainty in field and lab procedures (*Phoon 2018*). Probabilistic geostatistical
350 methods, especially kriging, address these limitations by offering linear, unbiased, and
351 minimum estimation variance, making them widely adopted (*Che and Jia 2019*). The
352 proliferation of ML has given rise to numerous data-driven methods which effectively integrate
353 sparse observation data and prior knowledge in geotechnical site characterisation, an example
354 of which is shown in Figure 9. Approaches such as iterative convolution XGBoost (*Shi and*
355 *Wang 2021a, 2023*), multiple point statistics (*Wang et al. 2022b; Zhou et al. 2024a; b*), sparse
356 Bayesian learning, hierarchical Bayesian modelling, Gaussian process regression (*Yoshida et*
357 *al. 2021*), and geotechnical Lasso (*Phoon et al. 2022b*) have been shown to be capable of
358 automatically improving geotechnical site characterisation results. Object oriented parametric
359 geological modelling using conditional random fields approach has also been explored (*Xie et*
360 *al. 2023*). These data-driven models automatically improve as the measurement dataset grows,
361 reducing the influence of prior knowledge on geotechnical site characterisation over time.
362 However, these approaches are complex for practical application and require further research
363 and development. Access to real-world data to develop and test reliable models, data
364 standardisation and protection remain crucial to address these challenges (*Phoon et al. 2023*).



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366 *Figure 9: Ground model developed from sparse data using CNN based iterative interpolation;*
 367 *reproduced from Shi and Wang (2021b)*

368 **4.2 BIM integration of site investigation and geospatial data**

369 Ground models, representing the subsurface in a BIM environment, provide a better quality of
 370 geological prognosis and also enable visualisation and coordination among all stakeholders
 371 (*Berdiglyjov and Popa 2019*). The first step in building the ground model is the integration of
 372 geotechnical and geological site investigation data into BIM for visualisation and stratigraphy
 373 analysis. These models requires constant updates using new geological, hydrogeological, and
 374 geotechnical information (*Klinc et al. 2021*). Acknowledging the dynamic nature of ground
 375 conditions throughout site investigation, design, and construction phases, automation with
 376 seamless interoperability of data across various formats becomes imperative for developing a
 377 high-fidelity DT of the underground space.

378 Currently, manual entry of paper-based borehole log reports into 2D/3D drafting tools is
 379 common; subsurface geological cross-sections are subsequently developed by drawing lines or
 380 splines to connect adjacent boreholes (*Shi and Wang 2021a*). Inherent uncertainties coupled
 381 with heterogeneity of the ground strata make the modelling process highly challenging.
 382 *Erharter et al. (2023)* proposed a framework for splitting the model into factual model,
 383 geotechnical model, and geotechnical synthetic modelling. AGS (Association of Geotechnical
 384 and Environmental Specialists) is a standard data format designed to enable information
 385 exchange across different geotechnical software systems with data structures to store

386 information such as borehole data, laboratory, and field tests (AGS 2023). Geospatial data are
387 available in digital standards like Open Geospatial Consortium (OGC) or CityGML, facilitating
388 the exchange of geological map data, time scales, boreholes, and laboratory metadata (“OGC
389 *Geoscience Markup Language (GeoSciML)*” n.d.). OGC is extending schemas to integrate
390 geotechnical models to maintain a common concept for the geology/geotechnics domain that
391 will be implemented by both IFC and OGC standards in the future (Fonsati et al. 2023). Despite
392 various open formats, there is a lack of integration of the geotechnical/geological data with the
393 BIM system. Converting data between formats poses interoperability and data preservation
394 challenges (El Sibaii et al. 2022; Fonsati et al. 2023) causing reduced effectiveness of the
395 ground modelling process. While custom workflows (e.g. El Sibaii et al. 2022) have
396 endeavoured to address these issues by proposing standardisation through product data
397 templates, the need for data format standardisation across the industry still remains as a
398 challenge.

399 For seamless integration of the ground models with BIM, accurate 3D visualisation of the
400 resulting ground conditions is essential. Representation methods for 3D geological models fall
401 into two primary categories: bin-based representation (triangulated irregular network and
402 boundary representation) and voxel-based representation (Borrmann et al. 2022). A
403 comparative analysis of these representation types is outlined in Table 3, which aids in
404 understanding the strengths and limitations of each type based on various criteria. From the
405 literature, recent research attempting BIM-based ground modelling are summarised in Table 2
406 along with their main features. Various tasks necessitate distinct forms of model
407 representations. For example, surface-based models are best for visualisation and planning,
408 while volumetric models are needed to capture the detailed spatial variability and material
409 properties essential for accurate simulations and risk assessments. A comprehensive ground
410 data management system that integrates and updates multiple representations in real time is
411 crucial to address this issue, providing accurate and accessible information for everyone
412 involved (Hegemann 2015). While Table 3 highlights the benefits of adopting a voxel-based
413 representation, Table 4, which ranks ground modelling representations from the literature based
414 on visualisation and analytical methods, reveals gaps in research. Specifically, there is a need
415 for data-driven methods combined with voxel representation in BIM and for hybrid models
416 capable of merging and converting different methods.

417

Table 3: Comparison of various 3D representation methods

Feature / Model Representation	TIN (Triangulated Irregular Network)	BRep (Boundary Representation)	Voxel (Volumetric Pixel)
Type of model	Surface-based	Surface-based	Volume-based
Geometry	Polygonal facets (triangles)	Polygonal facets (various shapes)	Cubes or rectangular blocks
Complexity handling capacity	High	High	Moderate (Resolution dependent)
Ability to hold semantic data	Data related to surface	Volumetric data	Volumetric data
Computation Time	Moderate	High	High (due to large data)
Detail Level	Surface detail only	Surface detail only	Internal detail (volumetric)
Spatial Variability Capture	Low	Low	High
Interoperability	IFC scheme available	IFC scheme available	Expected in IFC 4.0
Resolution Management	Fixed by triangle size	Fixed by facet size	Adjustable (Through voxel size and hierarchical structure)
Advantages	Flexible, efficient for complex surfaces	Accurate for boundary details	Detailed internal properties, adaptable resolution
Disadvantages	Non-smooth approximation	High complexity, high computation	High data storage, complex merging, and processing

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Table 4: Compilation of ground modelling representations from the literature, ranked based on visualisation method adopted with corresponding analytical methods for modelling

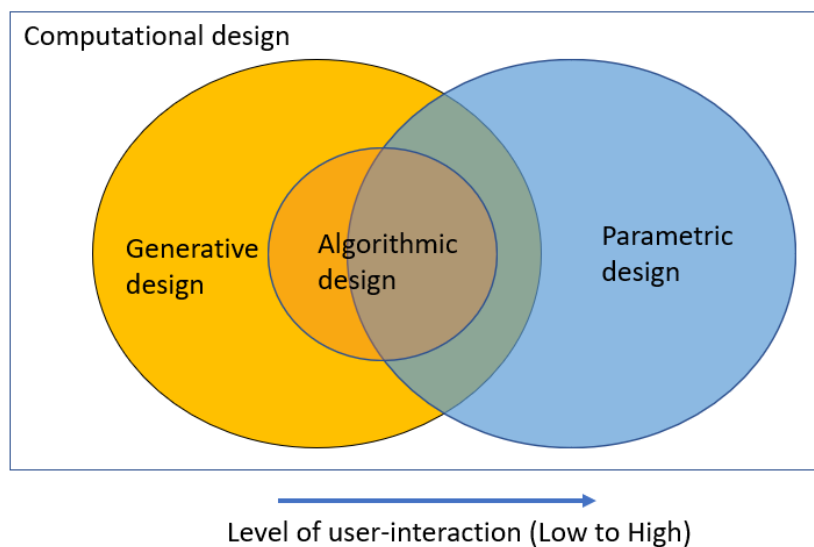
Reference	Visualisation method	Analytical method	Project	Software
(Che and Jia 2019)	TIN	Weighted kriging	Qianjiaying Coal Mine, Tangshan, China	Not disclosed in the article
(Fabozzi et al. 2021)	TIN	Spatial interpolation	Naples underground Line 1 and 6	Bentley OpenRail designer
(Huang et al. 2022)	TIN	Spatial interpolation	Not specified – Example demonstration	Revit, Dynamo
(Wang et al. 2022a)	TIN	Kriging Interpolation	Liangshuijing Tunnel	Civil 3D, Revi, Dynamo
(Xie et al. 2023)	TIN	Ordinary Kriging, uncertainty quantification using Conditional Random Fields	Not specified – Example demonstration	Revit, Dynamo
(Li et al. 2022)	BRep	Spatial interpolation	Suki Kinari underground powerhouse caverns	Catia
(Haryono et al. 2022)	BRep	Propriety tool used for ground	Not specified	Leapfrog, Revit

		modelling requiring manual input to BIM		
(Hung et al. 2022)	Propriety tool is used for ground modelling which must manually be input to BIM models		Taipei mass rapid transit project	GMS (Groundwater Modelling System):
(Hegemann et al. 2013; Koch et al. 2017)	Hybrid between BRep and voxel	Simple Kriging	Wehrhahn-Linie subway tunnelling project, Germany	X3dom, 3D CAD
(Mahmoudi et al. 2021)	Octree Voxel	Ordinary Kriging with uncertainty quantification using Optimal experimental design	Not specified – Example demonstration	Revit, Dynamo
(Khan et al. 2023)	BRep model, converted to voxel	Kriging Interpolation	Demonstrated with Peshawar city data	Revi, Dynamo, ArcGIS

422

423 4.3 Computational BIM

424 Computational BIM is a tool that integrates advanced computer processing with BIM, utilising
 425 algorithms and parameters to automate design solutions through a user-friendly visual scripting
 426 approach within the BIM environment (Wei et al. 2020). Parametric modelling is a process of
 427 creating models whose geometry and characteristics can be altered or manipulated through the
 428 adjustment of parameters (Edmonds et al. 2022). It serves as the fundamental building block
 429 for computational design, forming the basis for subsets such as parametric design, generative
 430 design, and algorithmic design, each offering different levels of user interaction (see Figure
 431 10Error! Reference source not found.).



432

433 *Figure 10: Subsets of computational design (incorporated from (Caetano et al. 2020))*

434 Generative design uses algorithms to automatically generate diverse design alternatives
435 iteratively based on predefined user input criteria with specific goals and penalty functions (*Ma*
436 *et al. 2021*). Algorithmic design is a subset of generative design which demonstrates
437 traceability of options, indicating an evident correlation between the algorithm and the resulting
438 design. Parametric design, on the other hand, involves defining geometry through parameters
439 and rules, enabling efficient modifications (*Caetano et al. 2020*).

440 Parametric design is increasingly used in the construction industry for design support,
441 automation, topology optimisation, design review and checking compliance to standards and
442 codes (*Sacks et al. 2020b*). Even in the field of geotechnical engineering, the application of
443 parametric modelling, is actively explored, particularly in research. For instance, *Koch et al.*
444 *(2017)* and *Ninić et al. (2020)* introduced a tunnel information modelling framework that
445 creates and connects the ground model, tunnel lining model, tunnel excavation model, and the
446 built environment. *Díaz et al. (2021)* demonstrated the use of generative design for automating
447 code-compliant design of a retaining wall. These approaches support efficient design and
448 process optimisation in conventional design, allowing for the exchange of information between
449 parametric analysis and numerical simulations with reduced computational effort
450 (*Hedayatzadeh et al. 2024*). *Ninić et al. (2024)* demonstrates a parametric modelling approach
451 for visualisation of ground settlements and building damage risk, enabled by integrating
452 empirical and analytical models using surrogate models. Computational BIM workflows which
453 (i) are integrated with geometric models, ground models and analytical models and, (ii) at the
454 same time, are able to modify those models based on real-time sensing data will be crucial for
455 future underground DT development. A lower level of user interaction, enabled by generative
456 design through BIM and multi-modal data, leads to the advancement of more mature predictive
457 and prescriptive DTs.

458 The use of Computational BIM in underground construction for the construction and
459 operational phases has been relatively underexplored in existing literature. Nevertheless, some
460 researchers have attempted to leverage computational BIM to integrate real-time sensor data
461 with BIM models, aiming to facilitate BIM-based structural health monitoring and
462 visualisation. For example, *Chang et al. (2018)* developed a platform that translates sensor data
463 into visual outputs using color-coded representations within BIM models. Similarly,
464 *Valinejadshoubi et al. (2019)* proposed a framework for transferring real-world sensor data into
465 BIM, allowing for the detection and visualisation of structural damage through colour coding,

466 utilising computational BIM tools. *Davila Delgado et al. (2018)* combined fibre optic sensor
467 data with BIM, employing color-coded visualisations and dynamic charts to depict structural
468 deformations. This integration was achieved using an external gaming engine software, which
469 communicated with the BIM model via computational BIM tools. Additionally, *Boddupalli et*
470 *al. (2019)* introduced a framework for handling large volumes of vibration sensor data from
471 bridges, connecting the processed data with sensor parameters within the BIM environment.

472 **4.4 BIM-numerical modelling software interoperability**

473 Geotechnical analysis is a crucial step in the design of underground structures, which involves
474 the use of ground models and ground constitutive models for realistic simulations using various
475 computational methods e.g. FEM (*Wang and Tian 2023*). While FEM pre-processing steps are
476 mostly streamlined and automated, challenges arise in integrating geometry into numerical
477 models, where interoperability issues persist between BIM and numerically modelling software
478 (*Alsahly et al. 2020; Fabozzi et al. 2021; Giangiulio et al. 2023; Klinc et al. 2021; Lou et al.*
479 *2021*).

480 The process of creating 3D geometry for numerical models involves importing information
481 through various file formats such as .dwg, .ifc, and cloud points. Manual operations are often
482 necessary for model definition, posing challenges for efficiency and accuracy (*Wu et al.*
483 *2022a*). Some researchers (*Fabozzi et al. 2021; Huang et al. 2022; Ninić et al. 2019a;*
484 *Tschuchnigg and Lederhilger 2020*) have attempted to automate these steps by adopting
485 advanced Python scripting with structured data inputs but these steps can be challenging to
486 execute. For tunnelling applications, *Ninić et al. (2021)* introduced an integrated framework,
487 employing a “BIM-to-FEM” approach through a custom platform (“SATBIM”), where
488 parametric modelling and numerical analysis were adopted to minimise user interaction and
489 real-time analysis capabilities, albeit requiring substantial programming effort. *Huang et al.*
490 *(2022)* proposed a BIM-to-finite differences method workflow for multi-LOD underground
491 metro stations, which enhances interoperability, automation, and error-free design-to-design
492 process to effectively explore design solutions and construction optimisation.

493 The challenges of mesh dependency and need for remeshing in FEM while importing from
494 BIM can be addressed by adopting iso-geometric analysis framework proposed by *Ninić et al.*
495 *(2020)*. With this approach higher order geometry in BIM can be directly utilised to create high
496 order computational models. Recent studies have demonstrated the reduction of computational
497 time by up to ten times (whilst maintaining accuracy) by adopting this approach (*Bui et al.*

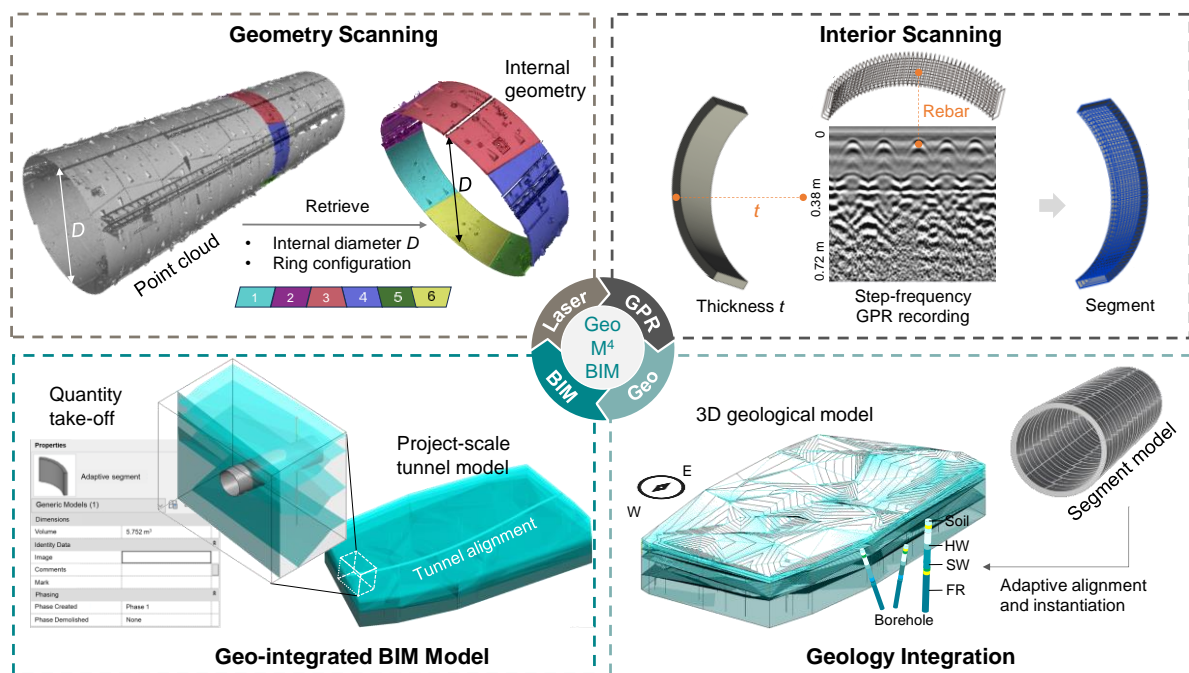
498 2024). The choice of geometry representation significantly affects FEM mesh quality and
499 flexibility during creation. Transitioning from analytical to discretised geometry in FEM mesh
500 preparation must align with model requirements for specific analysis. However, pre-discretised
501 geometry, like the triangulated model in IFC, limits flexibility, potentially making the FEM
502 mesh unsuitable. Insufficient or excessive density in discretised geometry points can lead to
503 distortion or numerical challenges. Unsuitable geometry may also introduce issues during the
504 transfer of 3D elements to 2D or 1D. Various representations, such as explicit geometry with
505 faceted B-Rep, triangulated face sets, procedural geometry with a swept profile, and octree or
506 voxel-based volume geometry, pose challenges for discretisation (*Eastman 2011; Huang et*
507 *al. 2022*).

508 The disconnect between BIM and numerical analysis programs inevitably leads to repeated
509 manual adjustments, highlighting the need for interoperability to enhance cross-disciplinary
510 coordination and workflow efficiency. (*Klinc et al. 2021*). Several case studies have
511 highlighted the data integration problems resulting from inconsistent information types and
512 data formats (*Fabozzi et al. 2019; Klinc et al. 2021*). Whenever modifications occur, a new
513 model is created using disparate geometrical representation and parameterisation native to the
514 numerical modelling program instead of directly referring to the as-designed or as-built BIM
515 model. The temporal changes in the ground behaviour due to the stages of construction and the
516 impact of long-term effects like consolidation, creep, etc., must be analysed by simulating the
517 distinct phases of the project. These processes become cumbersome with manual iterations
518 (*Giangiulio et al. 2023; Huang et al. 2022*). Leveraging the IFC scheme to enable seamless
519 FEM-BIM integration, even in the case of 4D simulation, is a key requirement for underground
520 DTs which should be explored further (*Li et al. 2020; Satyanaga et al. 2023*).

521 **4.5 Sensing and monitoring**

522 Traditional drawbacks of sensing and monitoring in underground construction include a lack
523 of sensor robustness, time-consuming installation and post-processing, and discrete and noisy
524 measurements (*Hong et al. 2022*). In particular, fibre optic technology has enabled
525 unprecedented real-time distributed strain and temperature monitoring of large infrastructure
526 (e.g. *Soga and Luo 2018; Suhail 2017*) as well as novel approaches for the ground-structure
527 contact stress sensing (*Templeman and Sheil 2024*). Micro electromechanical system (MEMS)
528 is another promising high-precision, low-power wireless technology (e.g., for measuring
529 inclinations), and IoT integration enables smart sensing networks (*Royston et al. 2022*).
530 Scalability of measurement can also now be achieved using computer vision techniques when

531 coupled with laser scanning (e.g. LiDAR) and imaging (e.g. using drones) which can help
 532 identify defects and deviations in structures (Huang et al. 2021; Lin et al. 2024; Romanovich
 533 et al. 2021). In situations where expansive areas need monitoring, Interferometric Synthetic
 534 Aperture Radar technology becomes particularly advantageous providing a holistic view of
 535 ground deformation and subsidence with minimal on-site instrumentation (e.g., Bayaraa et al.
 536 2023). Geophysical techniques like GPR are used to detect geological discontinuities and
 537 assess defects such as voids and delamination in underground structures through dielectric
 538 properties. Figure 11 describes a framework where the GPR scan data is integrated with BIM
 539 models (Zhu et al. 2024).



540
 541 *Figure 11: BIM centred modelling by laser scanning and GPR scans reproduced by (Zhu et al. 2024)*

542 Owing to the inherent non-linearity in ground-structure interaction, the fields of system
 543 identification and inverse analysis are leveraging artificial neural networks and physics-
 544 informed machine learning (Jafari 2020; Ouyang et al. 2024). These approaches aim to
 545 establish a digital nervous system for structures, facilitating accurate modelling of their
 546 behaviour. These advancements pave the way for the development of underground DT with
 547 optimised sensor utilisation.

548 5 LINKS BETWEEN OBSERVATIONAL METHOD AND DT CONCEPTS

549 The Observational Method (OM) in geotechnical engineering, introduced by Peck in 1969, is
 550 a dynamic 'learn-as-you-go' process that spans design, construction control, monitoring, and

551 review, aiming to reduce uncertainties and ensure efficient, yet safe, designs (Spross 2014).
552 Application of OM can take two forms:

553 (1) “ab initio” or from the start: involves initiating OM from project inception with the
554 most probable design values and contingency measures for deviations.

555 (2) “Ipso tempore” or the best way out: involves adaptability to unforeseen challenges
556 during construction to prevent catastrophe (*Spross and Johansson 2017*).

557 Several case studies highlight the benefits of the OM in geotechnical engineering, including
558 improved construction control, enhanced safety, and collaboration between designers and
559 constructors (*Nicholson 1999*). OM application has demonstrated substantial savings,
560 especially in temporary works and construction method optimisation, impacting both
561 temporary and permanent structures (*Powderham 2002*). Notable projects like the Heathrow
562 airport terminal building and several stations of the Crossrail projects have exemplified the
563 advantages of OM (*Chen et al. 2015; Gaba et al. 2017; Hardy et al. 2021; Powderham and*
564 *O’Brien 2021; Yeow et al. 2014*).

565 In the context of design approaches, CIRIA C185 (*Nicholson 1999*) elucidates the principles
566 and applications of OM, thereby presenting an opportunity for design optimisation (*Hardy et*
567 *al. 2018*). Eurocode 7 (*CEN 2004*) includes OM as an accepted alternative verification method
568 for conventional design of geotechnical structures. The code emphasises an adaptive
569 geotechnical approach, with principles focusing on continuous monitoring, pre-construction
570 planning, and prompt contingency actions as necessary, ensuring compliance in OM
571 application (Spross 2014).

572 **5.1 Recent advancements in OM**

573 Advancements in sensing and computational technologies have propelled OM from basic
574 onsite observations to sophisticated instrumentation and computer-based back analysis
575 techniques. Variables of interest may be measured directly (e.g., displacements) or indirectly
576 (e.g., stresses) through back-analysis using mathematical models such as FEM. The evolving
577 state of the system as construction progresses adds complexity to the back-analysis. In this
578 context, a practical approach involves probabilistic design with a Bayesian perspective on
579 statistics (*Huber 2016; Mohammadi and Parsapour 2024; Spross 2014*). For example, recent
580 work by *Jin et al. (2021)* employed the Markov chain Monte Carlo technique to estimate an
581 improved set of (posterior) ground parameters given a prior assumption (original design model)
582 and new evidence (monitored data). Such techniques have also helped to overcome over-

583 reliance on the monitored data by using prior distributions over model parameters. Sensitivity
584 analysis of monitored variables provides a rational approach to account for geotechnical
585 uncertainties. However, this process can be computationally expensive, especially when
586 sophisticated numerical models are involved with repeated simulations (e.g. *Li et al. 2018*).

587 To guide the decision on utility and safety of applying OM, *Roper et al. (2024)* introduced a
588 risk-based decision framework that uses expected utility theory, integrating risk, cost,
589 construction timelines, and engineering judgment within an economic decision model through
590 a probabilistic approach. Further advancements include the integration of ML with numerical
591 analysis (*Mitelman et al. 2023*). Considering the time and stage dependant behaviour of
592 underground structures *Bismut et al. (2023)* formalised a geotechnical problem as a sequential
593 decision problem and applied a heuristics-based method to finding optimal strategies. These
594 analytical techniques can be viewed as a simplified form of a preconstruction DT, establishing
595 a connection between the physical object and digital models. To become a true DT, models
596 must continuously and automatically update based on on-the-fly site data from the physical
597 object flowing into the virtual prototypes of the structure.

598 **5.2 Challenges in the application of OM**

599 While the OM presents several advantages for the construction industry, its broader adoption
600 faces many challenges; primary factors leading to stakeholder hesitancy include (a) the absence
601 of a standardised implementation code, (b) effort required for implementation, and (c)
602 misconceptions about heightened risk (*Hardy et al. 2018*), (d) lack of economic motivation due
603 to insufficient data/ quality of information in the early design stage. Traditional contractual
604 conditions, which often separate design and construction, impede a collaborative approach to
605 risk management (*Powderham and O'Brien 2021*). The iterative nature of the OM, especially
606 when addressing non-linear ground-structure interaction behaviours demands substantial time
607 and resources, and can be an obstacle to strict project timelines (*Hardy et al. 2018; Powderham
608 and O'Brien 2021*). Historical concerns regarding the accuracy and dependability of sensors
609 also fosters a perception of increased risk (*Spross 2014*).

610 **5.3 Complementarities between OM and DT**

611 Recent advancements in OM highlighted in section 5.1 have explored the integration of
612 advanced sensing technologies and ML. These technologies enhance data processing and
613 improve understanding of uncertainty in collected data through statistical analysis, which is
614 crucial for accurate multidisciplinary engineering evaluations. However, despite these

615 advancements, current practice still requires significant manual intervention for monitoring,
616 interpreting, and analysing site conditions, limiting the optimisation of design and construction.

617 Underground DTs offer a solution to these challenges by incorporating features that streamline
618 and automate many aspects of OM. Underground DTs provide capabilities such as real-time
619 data acquisition data integration, and advanced analytics and visualisation tools that enable
620 dynamic and continuous analysis of site conditions. These features reduce the need for manual
621 computations and facilitate the testing of various design scenarios, thereby optimising project
622 costs and mitigating risks. Furthermore, underground DTs address concerns regarding
623 measurement precision and instrumentation reliability through comprehensive sensitivity and
624 reliability analyses, which are essential for reassuring stakeholders and overcoming barriers to
625 the adoption of OM.

626 Table 5 outlines the synergies between the requirements of OM, as specified in Eurocode 7,
627 and the features of underground DTs. The table demonstrates how underground DTs can
628 enhance OM by supporting key activities such as establishing acceptable behaviour limits,
629 enabling continuous monitoring, and facilitating rapid contingency planning. Additionally,
630 underground DTs improve risk management and cost optimisation by addressing challenges
631 related to time constraints and the iterative nature of analysis. The integration of OM with
632 underground DTs can vary in levels of automation, ranging from descriptive twins that
633 primarily provide visualisation, to reflective twins that enable real-time model updates, and
634 further to advanced predictive and prescriptive twins. The latter more sophisticated
635 underground DTs can perform various types of analyses and offer recommendations, such as
636 design revisions or enhancements to monitoring protocols, thereby providing a more proactive
637 approach to managing construction projects. The full potential of advancements in OM
638 research can be realised by transitioning from conventional OM applications to integrated
639 predictive or prescriptive underground DTs.

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Table 5: Synergy between requirements of OM and features of underground DT

MATURITY DIMENSIONS		Prescriptive									
		Predictive									
		Reflective									
		Descriptive									
REQUIREMENTS AND CHALLENGES IN OM		FEATURES OF DT									
		Data integration and modelling	Multi-scale visualisation	Real time monitoring	digital model updating	Multi-physics analysis	Safety Assessment	Reliability & senility analysis	Cost optimisation simulations	Risk prognosis	Virtual control and generative design
REQUIREMENTS OF OM AS PER EUROCODE 7	Establish acceptable limits of behaviour as triggers	✓	✓								
	Assess range of possible behaviours	✓	✓								
	Establish monitoring for frequent update to enable contingency plan	✓	✓	✓				✓			
	Rapid monitoring to capture real time change	✓	✓	✓	✓						
	Define at contingency actions when trigger values exceed	✓	✓	✓	✓		✓				
	Continuous monitoring during construction	✓	✓	✓	✓	✓	✓				
	Assessment of monitoring to enable timely contingency action	✓	✓	✓	✓	✓	✓	✓		✓	✓
	Maintain reliability and quality of data	✓	✓	✓	✓	✓	✓	✓			
CHALLENGES IN OM APPLICATION	Insufficient time for design program	✓	✓	✓	✓	✓	✓	✓			
	Iterative recalibrated analysis process	✓	✓	✓	✓	✓	✓	✓			✓
	Contractual issue- sharing of risks and opportunities						✓	✓	✓	✓	
	Apprehensions of reliability and precision of instrumentation						✓	✓		✓	
	Apprehensions about safety of structure					✓	✓	✓		✓	

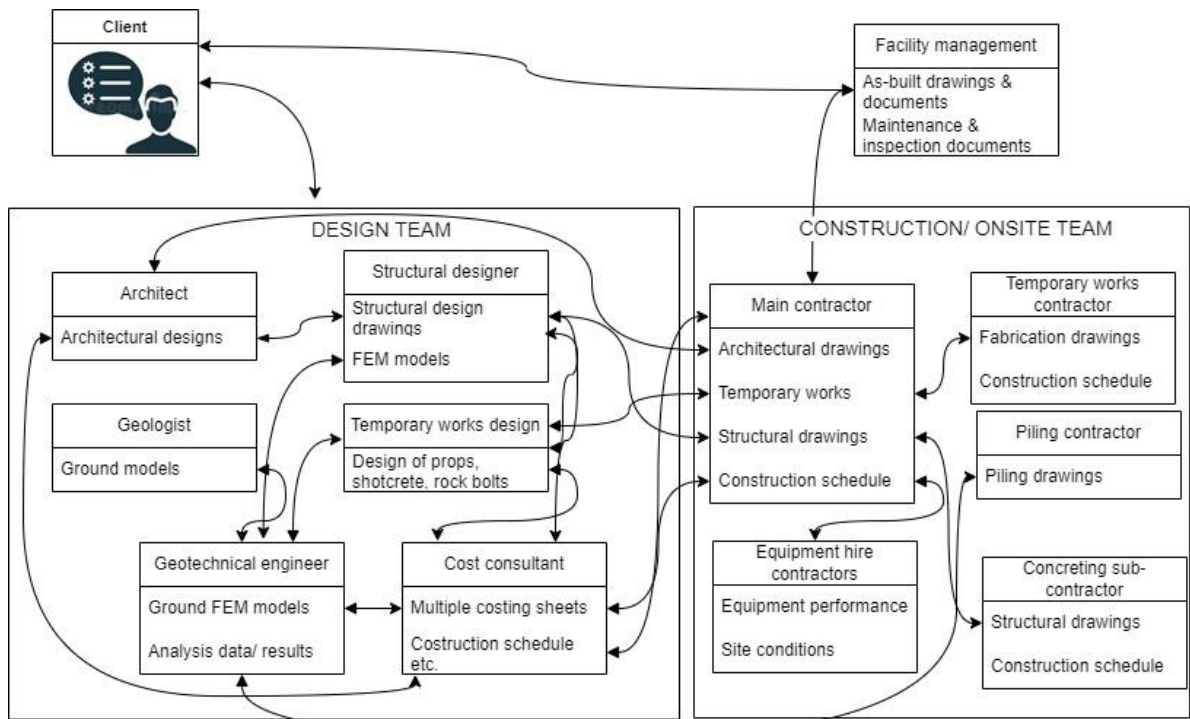
647 Despite the clear synergy, current research on OM has not considered application of DTs. A
648 co-occurrence map of keywords generated through a Scopus search of “*observational method*
649 *in geotechnical engineering*” lacks the keywords “*digital twin*” entirely, even though closely
650 related topics like computer simulations are evident (see Figure 12 **Error! Reference source**
651 **not found.**). These results highlight the significant gap in the existing literature exploring DT
652 application in the context of OM. To foster widespread growth of DT in geotechnical
653 engineering, there is a need for increased collaboration, particularly those focused on machine
654 learning, field monitoring, and OM.

673 and physical paperwork. This is particularly the case for buried utilities, where their
674 identification and diversion are a key challenge in underground construction. During
675 construction, data are also generated by various machinery (e.g., piling rigs) which is
676 undervalued in current projects, despite its potential to optimise both design and construction
677 processes. The presence of silos in the system hinders the full utilisation of automated data
678 collection (*Hoyme and Maurer 2021*). These uncertainties inherent in the conventional
679 approach contributes to the conservatism embedded in underground construction. Whereas the
680 underground DT approach breaks the information silos enabling real-time exchange of data
681 and on-the-fly analysis/ simulations capabilities as shown in the Figure 13b.

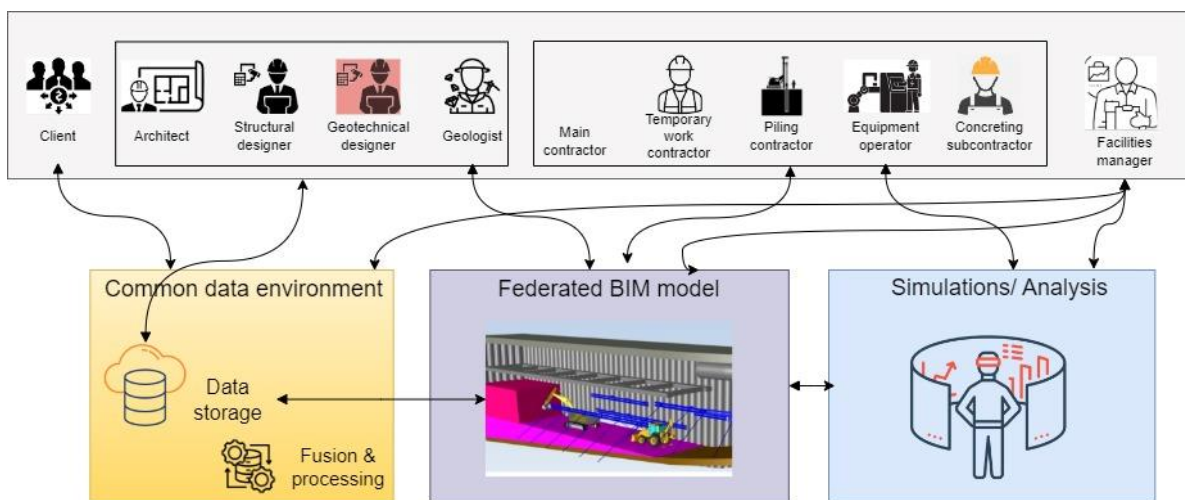
682 Figure 14 highlights the differences in uncertainty costs between conventional, BIM-based,
683 and DT approaches, due to information flow across project phases. Conventional methods, with
684 incremental data collection, face delays in real-time sharing and substantial information loss at
685 the end of each phase, resulting in higher uncertainty costs, as shown at point 'B'. On the
686 contrary, BIM-based methods improve information flow as described by *Borrmann et al.*
687 (*2018*) which involve sharing data among stakeholders, but real-time decisions are limited by
688 delayed data transfers. The dependence on subjective engineering judgment, coupled with
689 delayed and fragmented information, hinders timely evidence-based decisions. At each stage
690 there is a delay between discovery of findings and their communication to other stakeholders.
691 Most of the available information is also withheld until the end of each phase after the
692 information is transferred to the subsequent stakeholders in bulk. This bulk transfer of
693 information leads to an instantaneous drop in uncertainty cost at the end of each phase as
694 indicated as 'C' in the Figure. However, during the end-of-operations phase, the assessment of
695 reusability will involve various destructive and non-destructive tests which bring additional
696 uncertainty about the ground properties and structural condition, resulting in increased
697 uncertainty costs as shown in 'D'. Another advantage of BIM process, marked by point 'A', is
698 that it retains information from previous projects, reducing uncertainty at the start, unlike
699 conventional methods that begin with limited prior knowledge.

700 The DT approach, unlike conventional and BIM methods, in addition to eliminating the
701 information silos through real-time data exchange, the analysis capabilities of the DT with real-
702 time visualisation, machine learning, and analysis to reveal patterns and insights, enhancing
703 decision-making for downstream processes. This helps in significantly lowering uncertainty
704 costs throughout the project lifecycle (*Li et al. 2024a*). Continuous data flow supports timely

705 data collection and collaboration, enabling faster reductions in uncertainty compared to BIM.
 706 For example, the data collected in the ground investigation or pile load test data dynamically
 707 updates the ground models which helps to reduce the uncertainty in designs. Additionally, the
 708 application of observational method for automated analysis of data in real-time is enabled by
 709 the DT approach which is missing in the BIM approach. Due to which the uncertainty cost
 710 reduces at a higher rate. Despite this, residual risks remain due to project complexity and
 711 multiple stakeholder involvement.

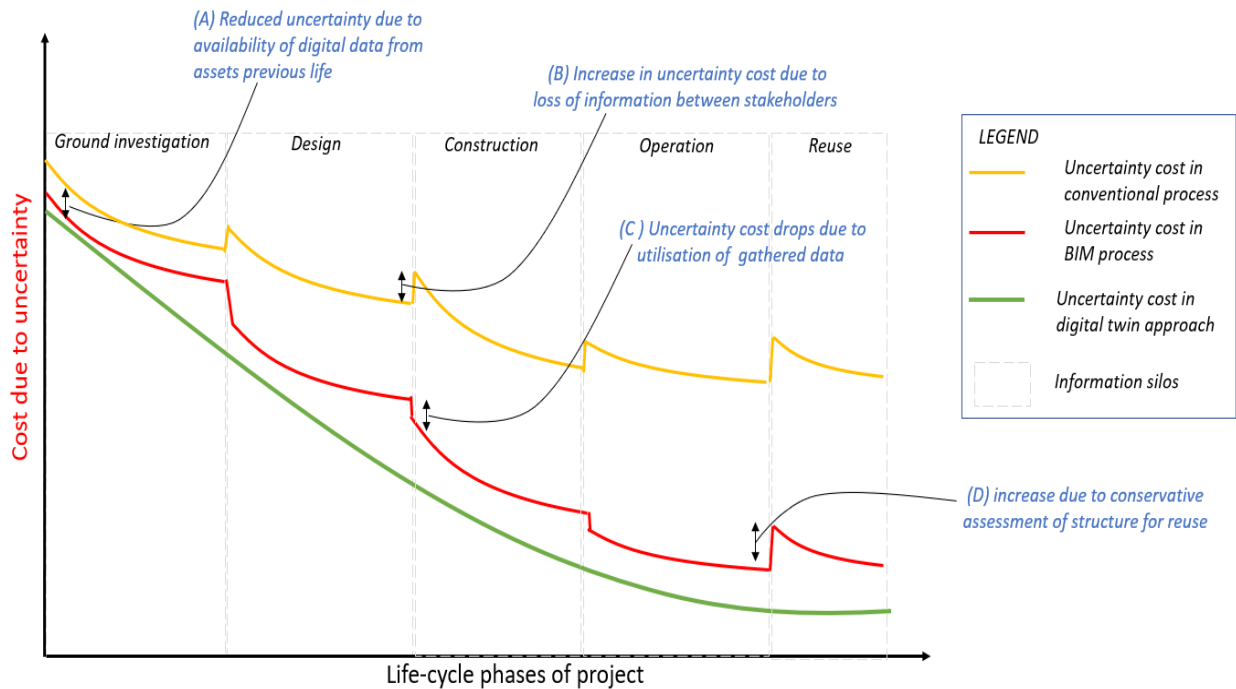


(a)



(b)

712 Figure 13: Information flow between stakeholders in (a) conventional process; (b) DT process



713

714 *Figure 14: Conceptual illustration of the uncertainty costs due to information silos in a conventional*
 715 *and BIM approach compared to that enabled by underground DTs*

716 **6.2 Risk prognosis and safety assessment during construction**

717 Underground construction faces several inherent risks which are exacerbated by uncertain
 718 weather, geological factors, and the hydrogeological environment. Human factors, like
 719 collisions with utilities during excavation, pose additional dangers which have led to several
 720 historical accidents (*Liu et al. 2023*). Environmental factors, such as rainfall and temperature,
 721 and factors such as uncontrolled dewatering (e.g. *Zeng et al. 2023*) can impact the safety of
 722 underground construction significantly.

723 Given changing ground conditions during construction, risk analysis and mitigation requires
 724 timely acquisition of spatiotemporal risk information for effective risk prediction. Current field
 725 practices rely on visual measurements and inspections, which are time-consuming and demand
 726 extensive field experience. FEM models based only on initial design documents often fall short
 727 in accurately representing as-built conditions during construction if not dynamically updated.
 728 Therefore, updating models using diverse data is crucial to establish a high-fidelity virtual
 729 model, enabling the examination of various unsafe scenarios through simulation approaches.
 730 A virtual model with geometric, physical, and behavioural components, integrating
 731 multidisciplinary knowledge, aids risk management.

732 Several case studies illustrate practical applications of intelligent foundation engineering and
733 risk prognosis of deep excavations using a DT approach. *Sun et al. (2023)* demonstrated the
734 application of a DT in a case study of Wuhan Metro Line 7, by capturing and processing diverse
735 information in the physical space through advanced sensing techniques and data processing
736 algorithms. Data analysis tools were developed to inform prognosis and control of unsafe
737 events during foundation pit excavation, allowing for risk assessment and introducing control
738 decisions for enhanced safety in the physical environment. *Cao et al. (2022)* assessed the risk
739 of tunnelling-induced building damage by combining FEM of tunnelling with building models,
740 accounting for ground-structure interaction, and using artificial neural networks for real-time
741 damage prediction. *Liu et al. (2023)* developed a computer vision-based approach for avoiding
742 accidents in excavation by analysing the position of excavators. By integrating DT, deep
743 learning and mixed reality technologies, *Wu et al. (2022b)* developed a real-time visual alarm
744 system that enables construction workers to proactively judge their safety status and avoid
745 accidents.

746 **6.3 Time, cost and carbon optimisation of underground construction**

747 Underground DTs have the potential to transform underground construction by optimising both
748 design and construction processes. Their key advantage lies in bringing diverse sources of data
749 from different domains, such as the environment, man-made structures, and archaeological
750 artefacts, into a unified framework using advanced analytics, numerical modelling, and ML to
751 perform real-time simulations and analyses. This enables continuous model refinement and
752 real-time design optimisation, providing a more holistic understanding of complex interactions
753 and facilitating multi-disciplinary optimisation of design and maintenance measures through
754 the simultaneous evaluation of different criteria and physics. For instance, *Xie et al. (2024)*
755 introduced a BIM-based multi-model framework designed to incorporate multiple LOD for
756 TBM machinery, 3D geological models, and numerical analysis models, enabling real-time
757 thrust calculations and predictive analysis of shield tunnelling. In terms of ground-structure
758 interaction (GSI), such as the pile installation, ground resistance and applied torque can be
759 transmitted to the underground DT, allowing automatic updates to the ground model. This
760 dynamic modelling enhances understanding of ground conditions, leading to more accurate
761 predictions of ground behaviour, and reducing the inherent uncertainty in geotechnical
762 engineering. As *Randolph (2003)* observed, even with advanced models, estimating axial pile
763 capacity can be challenging, often within $\pm 30\%$. But with underground DTs this uncertainty
764 can be reduced significantly, leading to safer and more cost-effective designs. Databases like

765 the DINGO project (*Voyagaki et al. 2022*) further improve statistical assessments of pile
766 performance. By simulating design scenarios using real-time data, underground DTs create
767 site-specific designs. Continuous response from the structures under varying loads informs
768 real-time adjustments, reducing uncertainty and aligning designs with actual conditions,
769 enhancing safety, and cutting costs. Moreover, underground DTs use historical and real-time
770 data to predict potential issues, such as faults in underground excavation and structures
771 installation before they escalate. ML models refine GSI predictions, minimising risks and
772 preventing delays. Future underground DT developments could integrate generative design,
773 allowing engineers to explore various scenarios and optimise foundations to site-specific
774 conditions, reducing on-site adjustments and costs. Additionally, underground DTs could
775 incorporate modular and prefabricated design elements, streamlining the construction process
776 and further cutting time and costs. *Huang et al. (2023)* integrated BIM to evaluate carbon
777 emissions and construction feasibility, including GSI assessment and the assembly process, in
778 prefabricated stations. *Chen et al. (2024)* expanded this digitalisation framework by
779 incorporating carbon assessment standards, numerical modelling, and optimisation techniques
780 to assess carbon emissions and establish benchmarks for TBM tunnel construction products
781 and processes. In tunnelling operations, underground space DTs can help in automated steering
782 of TBM operational parameters based on the data and models to minimise the environmental
783 impact.

784 **6.4 Lifetime monitoring of underground structures and assets**

785 Current maintenance practices for underground spaces and assets are predominantly reactive,
786 with excavation in urban areas often facing risks such as pipeline bursts, explosions, and safety
787 hazards. In the UK alone, accidental strikes on underground pipes and cables are estimated to
788 cost approximately £1.2 billion annually (*Wang and Yin 2022*). The adoption of DTs for
789 underground spaces can greatly enhance the value of these assets by delivering essential
790 information and services. In addition to adding value, continuous monitoring of foundation
791 structures is crucial but presents significant challenges, as these structures are rarely
792 replaceable and key areas are often inaccessible for visual inspection (*Bhalla et al. 2005*).
793 Underground structures pose unique challenges, including changing earth pressures,
794 construction-induced ground movements, underground formations, and fluctuations in
795 groundwater. Predicting the long-term behaviours of these structures during the design stages
796 is challenging due to the wide variety of surrounding geologic conditions and non-linear ground
797 properties (*Dutta and Kurup 2018*). As the ground around the structure undergoes temporal

798 changes, such as consolidation, the corresponding loads applied to the underground
799 engineering structure also change significantly. Moreover, the service life and safety of
800 underground structures are impacted by changes in geometric and material properties due to
801 operational incidents and the complexity of underground environmental conditions (*Abbas et*
802 *al. 2023*). Additionally, increased congestion in underground spaces means that the
803 construction of new underground structures can distort or damage existing underground
804 structures due to changing stresses in the ground (*Yu and Geng 2019*) and complex two-way
805 relationships (*Wan et al. 2023*).

806 Recent efforts to address these issues include sophisticated numerical models for mechanised
807 tunnelling and ground-structure interaction (*Boldini et al. 2018; Ninić et al. 2014; Yiu et al.*
808 *2017*). In addition, geophysics techniques like GPR are adopted to understand anomalies such
809 as voids and water leakage from buried utilities (*Zhu et al. 2024*). However, advanced 3D
810 computational models often involve extensive detail and prolonged computation times which
811 prompts parallelisation strategies for high performance computing (*Ninić et al. 2019b*).
812 Furthermore, the BIM framework has gained prominence in large infrastructural projects,
813 serving as a robust tool for information management, processing, visualisation, and analysis
814 across the project lifecycle. This is especially beneficial during the early design phases of
815 intricate multidisciplinary systems.

816 In existing monitoring systems, sparsely distributed point measurements are gathered around
817 structures to assess whether the recorded displacements surpass predetermined thresholds
818 established during design. Despite the widespread use of monitoring, concerns persist about
819 the effectiveness of conventional techniques due to the limited number of monitoring points
820 for each structure hindering accurate evaluation of actual building deformations. Moreover, the
821 reliability of damage inference using monitored displacement data and equivalent-beam
822 models is constrained due to data sparsity. Additionally, GSI response is influenced by the
823 extent of pre-existing cracking and distortions in the supported superstructure (*Acikgoz et al.*
824 *2022*). *Ninić et al. (2024)* proposed a BIM-based real-time prediction of non-linear structural
825 response using meta models for prediction of complex phenomena which includes assessment
826 of structural response in BIM. These recent developments coupled with lifetime monitored data
827 of the underground structure, will enable life-time monitoring using underground DT.

828 **6.5 Reuse of underground structures**

829 The concept of reusing old foundation structure is growing in popularity for its programme,
830 material, carbon, and construction cost savings. However, a major obstacle for reuse is the
831 uncertainty and risk associated with the performance of the old foundations (*Chapman et al.*
832 *2008*) even though research has shown that ageing can improve both foundation stiffness and
833 capacity (*Sheil 2017*). Non-availability of records with high reliability, indicating various key
834 details such as the foundation location, sizes, capacities, integrity, and structural details is
835 another challenge for evaluating the feasibility of reuse (*Taylor 2020*). Unknowns, such as
836 unidentified construction defects and any deterioration that may have occurred after
837 construction, also increases risk (*Chapman et al. 2006*). Assessing foundation reuse feasibility
838 involves collaborative decision-making between geotechnical engineers, structural engineers,
839 architects, construction engineers, and other stakeholders based on the analysis of the previous
840 records, estimates of the remaining service life of the foundations, prediction of settlements
841 and various design options proposed for the new superstructure.

842 The current method of evaluating the feasibility of reuse involves unreliable estimates of the
843 various parameters above, which leads to overly conservative designs to account for residual
844 uncertainties and risks. A DT of the basement structure will capture the system's data through
845 its entire lifecycle and provide real-time updates about the ground-structure interaction and
846 structural health of the structure, which are critical for the decision-making. This will be a novel
847 solution to address the risks associated with basement/ underground construction reuse. The
848 rich data will also help in predicting the behaviours of the structure and surrounding ground
849 for various current and future design scenarios.

850 **7 LIMITATIONS OF THE STUDY**

851 The components of the underground DT architecture presented in Figure 4 are not exhaustive.
852 For example, the physical entities and processes layer could encompass additional elements,
853 such as structural components from neighbouring constructions. Similarly, the application
854 layer could offer a wider range of features and analytical capabilities. The conceptualisation of
855 the digital twin architecture in this study focuses on features and applications that are
856 commonly adopted in current industry practices. However, DTs can reach higher levels of
857 maturity, such as autonomous twins (beyond prescriptive twins), in industries like
858 manufacturing and aerospace. These advanced twins are enabled by automated decision-
859 making and actuation. Since DTs for underground space are still in their infancy, this study
860 does not cover specific use cases of these advanced features. For instance, an example of

861 autonomous digital twins in underground construction could be autonomous excavators that
862 operate based on design models and real-time feedback from computer vision data. While such
863 developments are progressing in the mining industry, they are not explored here in the context
864 of urban underground construction. Additionally, this study focuses only on a few exemplary
865 high-level use cases of digital twins to demonstrate their immediate value. Although there are
866 numerous emerging areas influencing the development of DTs—such as research on data
867 fusion and the application of blockchain technology for secure information management – this
868 study prioritises the most pertinent areas identified in the literature from underground space
869 and construction.

870 **8 CONCLUSIONS**

871 The expansion of underground construction presents a myriad of challenges, involving low
872 productivity, prolonged construction timelines, heightened costs, safety concerns, and
873 uncertainties in ground conditions. These obstacles collectively impede the overall efficiency
874 of underground construction processes. However, DTs emerge as a promising solution,
875 offering potential benefits such as real-time monitoring and visualisation, improved
876 collaboration, intelligent operation throughout the lifecycle of the structure.

877 In the current landscape, there exists a considerable degree of ambiguity surrounding the
878 concept of DTs, which vary depending on the context and the sector. Given the intricate
879 challenges inherent to underground spaces, a distinct definition and maturity framework for
880 underground DT are imperative. This definition should also identify the specific use cases of
881 underground DTs. Such clarity facilitates the definition, management, integration, and
882 optimisation of underground DTs, enabling both academic and practical benchmarking of
883 projects and technology systems. Establishing clear definitions and identifying features and
884 derived value, enables benchmarking with other sectors allowing the geotechnical community
885 to draw inspiration from diverse developments.

886 With the context of underground DTs, a spectrum of possibilities and variations are possible
887 with varying dimension of maturity ranging from basic descriptive twins to sophisticated
888 prescriptive twins. Each dimension is further capable of differing levels of advancement based
889 on specific applications and expected value. A layered architecture serves as a generic
890 framework for building an underground DT. The maturity of a particular underground DT
891 hinges on factors like model quality and completeness, stakeholder interaction, fidelity and

892 automation levels, and federation degree, ranging from basic prescriptive twins to advanced
893 iterations.

894 Research in underground space has explored areas such as machine learning, BIM-FEM
895 interoperability, and GIS integration, revealing applications such as data-driven ground
896 modelling, predictive ground behaviour modelling, and real-time monitoring of geotechnical
897 structures. Despite their potential to enhance accuracy, efficiency, and safety, practical
898 implementation of these advancement in real projects faces challenges due to technical
899 complexities and scepticism with black-box application of technologies like ML. Addressing
900 these issues entails providing researchers access to real-world data to refine models and
901 integrating disparate technology developments through a DT approach, which mitigates
902 stakeholder interaction and process silos.

903 Although research and technology development are ongoing, the adoption of digital twins for
904 underground spaces faces significant management and regulatory barriers due to low
905 technology readiness levels. Key challenges include complex stakeholder coordination, high
906 upfront and maintenance costs, data integration issues, and a lack of specialised skills.
907 Additionally, barriers such as data standardisation, privacy, and security concerns must be
908 systematically addressed.

909 By integrating the underground space DTs in readily adaptable solutions like OM, the benefit
910 of this technology is realised by the broader geotechnical community while the above obstacles
911 will be gradually overcome. Currently, OM involves frequent monitoring and model updates
912 based on trigger values, functioning as a basic descriptive twin. By focusing ongoing OM
913 research on advanced instrumentation and computer-based back analysis within an integrated
914 DT approach, the practice can evolve into a more mature, prescriptive, knowledge-based DT
915 system. To fully leverage UGDTs' potential across all lifecycle stages of underground
916 structures, professional bodies and the geotechnical community should adopt a holistic
917 approach to integrating other technological advancements with DTs.

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923 **10 DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN** 924 **THE WRITING PROCESS**

925 During the preparation of this work, the first author used Grammarly and ChatGPT to review
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