

AN IMPLEMENTATION FRAMEWORK FOR AI-ENHANCED 3D MAPPING

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Abstract

Artificial Intelligence (AI) is revolutionising three-dimensional mapping in the civil infrastructure sector. Terrestrial Laser Scanners, GNSS RTK and Robotic Multi-stations are enhanced by AI technologies that assist with data processing, spatial accuracy, and make it easier to monitor infrastructure development. The infrastructure sector in South Africa faces significant implementation barriers. The theoretical framework underpinning the study focuses on the Diffusion of Innovation Theory, highlighting the implementation of AI-enhanced 3D mapping across the sector. Identified articles on AI integration and implementation in the civil infrastructure sector enables the study to systematically examine existing evidence on the adoption, applications, opportunities, and challenges of AI. This approach facilitates the synthesis of current knowledge, identification of research gaps, and development of insights into factors affecting the successful implementation of AI in civil infrastructure. Atlas.ti facilitated a thematic analysis of 50 papers. While the review identified a significant knowledge gap regarding AI-integrated technology systems in South Africa, the underlying causes of this gap were not explicitly established. One explanation is the recent adoption of AI technologies within the sector, with AI being noted for its automating feature extraction, improving terrain models, helping build digital twins, and enabling predictive maintenance. Resulting in faster operations, less manual work, and stronger decision-making. Implementation barriers hinder the success of the AI-Implementation Strategy for South Africa, which is based on phased rollouts, collaboration, workforce training, and clearer policy standards. The study concludes that AI can enhance civil infrastructure efficiency and decision-making while providing a phased implementation roadmap.

Keywords: Artificial Intelligence, 3D mapping, Civil works, Digital infrastructure, Geomatics, South Africa

1. Introduction

The civil engineering sector has undergone significant technological transformation through the adoption of AI, automation, and digital technologies, enhancing efficiency, infrastructure management, and decision-making processes (Manzoor *et al.*, 2021; Xu *et al.*, 2022). The integration of geospatial data, Building Information Modelling (BIM), digital twins, and predictive analytics has improved project planning, monitoring, and asset maintenance throughout the infrastructure lifecycle (Nyokum & Tamut, 2025; El-Abbasy, 2025). As infrastructure supports economic growth, urban functionality, and regional connectivity, smart mapping has become increasingly important (National Planning Commission, 2020). However, traditional surveying methods remain limited by time and resource requirements when processing large and complex datasets (Aouad *et al.*, 2018). AI-enhanced 3D mapping enables civil engineering teams to use laser scanners, drones, robotic total stations, and GNSS platforms to automate feature identification, terrain analysis, defect detection, and infrastructure assessment (Shirowzhan *et al.*, 2020). These advancements have increased the practicality of digital

construction approaches, including BIM, digital twins, and smart infrastructure systems (Bolton *et al.*, 2018). The global AI construction market is projected to grow from approximately USD3.02 billion in 2026 to USD 9.48 billion by 2030, driven by demand for improved infrastructure monitoring, cost optimisation, and sustainable infrastructure development (The Business Research Company, 2026; Grand View Research, 2025; Adebiyi *et al.*, 2024; Lu *et al.*, 2020). Despite these developments, South Africa's civil engineering sector continues to face challenges in adopting AI and digital technologies such as BIM. Adoption remains fragmented due to limited skills, high implementation costs, insufficient institutional support, resistance to organizational change, and inadequate digital infrastructure (Tjebane *et al.*, 2022; Calitz & Wium, 2022). Although interest in AI applications is increasing, research on the adoption and implementation of AI-enabled 3D mapping technologies within South African civil infrastructure remains limited (Tjebane *et al.*, 2022; Calitz & Wium, 2022). In this study, integration refers to the embedding and operational combination of AI techniques within 3D mapping systems to enhance spatial data

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acquisition, processing, analysis, and application in civil infrastructure projects.

2. Literature Review

The literature review examines AI-enabled 3D mapping in the civil sector. It is guided by diffusion of innovation theory, which explains how technological innovation influences efficiency, implementation, and digital transformation adoption within South Africa's civil sector (Lu *et al.*, 2020).

2.1 The Role of Artificial Intelligence in 3D Mapping for Civil Infrastructure

AI and machine learning have advanced geomatics and civil engineering by enabling efficient processing of complex spatial datasets for remote sensing, terrain analysis, infrastructure monitoring, point cloud

error during planning and execution (Ma *et al.*, 2019; Li *et al.*, 2021). AI-assisted monitoring supports defect detection, safety management, and lifecycle maintenance planning (Adebiyi *et al.*, 2024; Lu *et al.*, 2020; Zhang, 2021). Digital twins further support predictive maintenance through virtual infrastructure representations (Fuller *et al.*, 2020). However, adoption remains constrained by technical capacity, costs, skills shortages, interoperability challenges, and limited implementation strategies (Tjebane *et al.*, 2022; Calitz & Wium, 2022; Lu *et al.*, 2020; Adebiyi *et al.*, 2024).

2.3 Comparative Analysis of AI-Enhanced 3D Mapping Technologies

Different 3D mapping technologies offer varying operational capabilities in the civil sector. Table 1 presents an overview comparison of key technologies and AI applications.

Table 1: Comparative Analysis of AI-Enhanced 3d Mapping Technologies

Technology	AI Application	Main Advantages	Main Limitations	Civil Works
TLS	Point cloud classification	High spatial detail	Expensive processing	Urban roads and bridges
UAV Photogrammetry	Automated terrain modelling	Rapid area coverage	Weather dependent	Earthworks and corridors
GNSS RTK	Position optimization	Fast field deployment	Lower vertical precision	Open terrain surveying
Robotic Total Stations	Automated tracking	High layout precision	Requires line-of-sight	Structural and road layout
Mobile Mapping Systems	Real-time feature extraction	High mobility	Large data storage requirements	Transport infrastructure

Source: Adapted from Kim *et al.*, 2022

segmentation, feature extraction, and defect detection (Ma *et al.*, 2019; Zhu *et al.*, 2020). AI-enabled 3D mapping supports applications including road corridor mapping, pavement assessment, earthwork estimation, structural monitoring, digital terrain modelling, and asset management (Li *et al.*, 2020; Ma *et al.*, 2019; Zhu *et al.*, 2017). Technologies such as TLS and UAV photogrammetry generate point cloud data that AI classifies to improve maintenance planning, reduce risks, and enhance real-time engineering decision-making (Boje *et al.*, 2020; Li *et al.*, 2020).

2.2 Digital Transformation Enhanced by Artificial Intelligence in Civil Infrastructure

Digital transformation within the construction sector has accelerated through the Fourth Industrial Revolution, with AI operating alongside BIM, IoT, robotics, cloud computing, and geospatial analytics (Oesterreich & Teuteberg, 2019). AI integration with 3D mapping enhances infrastructure projects by automating spatial data collection, processing, and analysis, improving delivery efficiency (Li *et al.*, 2020; Zhu *et al.*, 2017). AI-driven systems improve surveying accuracy through automated feature extraction and high-precision spatial interpretation, reducing human

The literature indicates that integrated systems comprising multiple interacting components can outperform standalone systems due to complementarity, improved co-ordination, and enhanced system-level functionality. When you use intelligence to bring these systems together, they can share information and work together more easily. This is especially true for surveying platforms, where combining data from sources can yield more accurate results (Kim *et al.*, 2022). AI enables surveying platforms to work together and share data (Zhang, 2021).

2.4 Artificial Intelligence Adoption Challenges in South Africa

The South African civil infrastructure sector faces several barriers limiting AI implementation, including legacy systems, limited interoperability, skills shortages, excessive costs, inadequate digital infrastructure, and resistance to technological change (Tjebane *et al.*, 2022; Adekunle *et al.*, 2022). Training institutions remain focused on traditional surveying and engineering curricula, contributing to gaps in AI and geospatial analytics skills (Calitz & Wium, 2022; Tjebane *et al.*, 2022). Although digital transformation policies recognise the importance of AI, smart

infrastructure, and digital engineering, structured implementation frameworks remain limited (DCDT, 2021; PC4IR, 2020; Calitz & Wium, 2022). Organisations such as SANRAL and Transnet SOC Ltd have incorporated digital monitoring, geospatial technologies, and BIM-related practices into selected operations (SANRAL, 2017; Transnet SOC Ltd, 2020). However, adoption remains fragmented due to institutional capacity constraints, weak policy integration, and limited investment in digital construction and geomatics sectors (Zhang, 2021).

2.5 Diffusion of Innovation Theory

The Diffusion of Innovation Theory provides framework for understanding how technological innovations are adopted and integrated into professional systems through factors such as relative advantage, compatibility, complexity, and observability (Rogers, 2003; Shibeika & Harty, 2015). Within this study, the theory explains the adoption of AI-enhanced geomatics technologies, including TLS, MTS, and GNSS/RTK systems, within the South African road construction sector, where adoption is influenced by institutional readiness, skills availability, and organisational culture (Zhang, 2023; Oesterreich & Teuteberg, 2016). Research on construction digitalisation demonstrated that BIM, digital twins, and AI-enabled systems are being adopted unevenly due to differences in infrastructure capacity, policy support, and organisational maturity (Adebiyi *et al.*, 2024; Douglas *et al.*, 2021). The theory therefore highlights that perceived benefits of AI-based geomatics solutions alone are insufficient for successful integration, particularly in developing contexts such as South Africa where institutional capacity and technological readiness influence adoption outcomes (Lit *et al.*, 2020; Froise & Shakantu, 2014).

3. Research Methodology

3.1 Research Design and Data Collection

This study is grounded in an interpretivist research philosophy, as it seeks to understand how AI is applied

and integrated within 3D mapping and civil engineering contexts through interpretation of existing literature, focusing on meanings, practices, and contextual factors influencing its use in real-world settings. An inductive research approach was adopted, allowing themes to emerge from the reviewed studies rather than testing predefined hypotheses. A qualitative methodology was applied, with thematic analysis used to identify, compare and interpret recurring patterns related to AI applications in geomatics and infrastructure development. The research strategy was a systematic literature review focusing on peer-reviewed academic sources, industry reports, and policy documents. The study adopts a cross-sectional time horizon, focusing on literature between 2010 and 2026 to capture developments in AI applications and integration within 3D mapping and civil engineering contexts (Saunders *et al.*, 2019). Secondary data were collected from peer-reviewed journal articles, conference papers, government policy documents, industry reports, and academic books relating to geomatics and infrastructure development. Literature was retrieved from academic databases including Scopus, Web of Science, and Google Scholar using search terms such as “Artificial Intelligence,” “3D Mapping,” “Geomatics,” “Civil Engineering,” “Digital Construction,” “Infrastructure Monitoring,” and “South Africa”. The review focused primarily on studies published between 2015 and 2026 to capture contemporary developments in AI applications within engineering and geomatics disciplines. Literature selection was guided by relevance to AI applications in surveying, infrastructure monitoring, and civil engineering practice, ensuring a focused and contextually aligned dataset (Page *et al.*, 2021).

3.2 Systematic Literature Review

A structured literature review was conducted in accordance with the PRISMA 202 guidelines to ensure a transparent and systematic study process (Page *et al.*, 2021). The review (Figure 1) identified 1,200 records, with 200 duplicates removed, leaving 1,000 studies for screening. After title and abstract screening, 190 full-

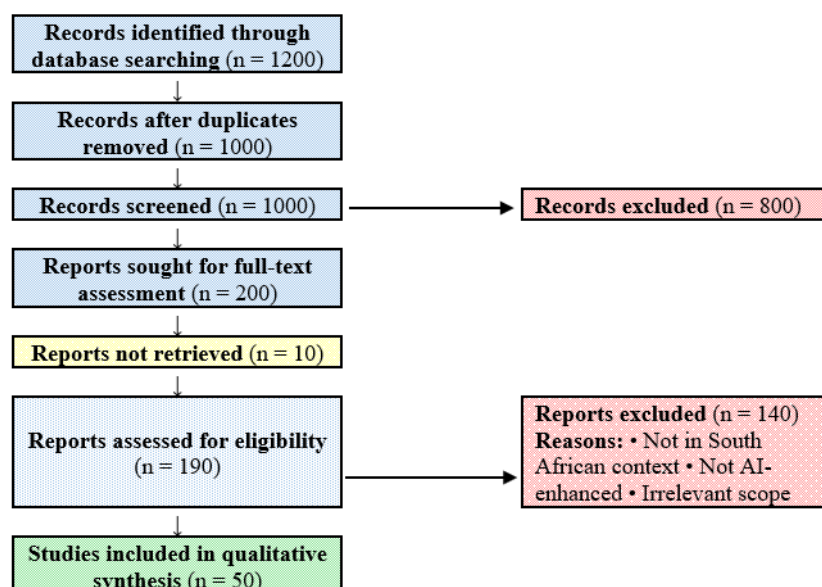


Figure 1: Prisma Flow Diagram

text articles were assessed for eligibility, resulting in the inclusion of 50 studies. Studies were excluded if they did not address AI applications in civil engineering or geomatics, lacked relevance to infrastructure mapping and surveying technologies, or fell outside the study scope. Both researchers independently assessed studies for eligibility, methodological clarity, relevance and reproducibility. The final studies were analysed using thematic analysis (Page *et al.*, 2021). Quality assessment also considered contributions to AI-driven surveying and infrastructure monitoring, particularly to use of TLS, MTS, GNSS/RTK systems and digital construction platforms. These criteria improved consistency, reduced selection bias and strengthened the validity of the review findings (Kitchenham *et al.*, 2015; Moher *et al.*, 2015).

3.3 Comparative Thematic Analysis

Thematic analysis was employed to systematically analyse, interpret, and identify patterns within the qualitative data using the six-phase framework developed by Braun and Clarke (Braun & Clarke, 2019). The collected literature was analysed to identify recurring patterns, concepts, and trends relating to the application of AI in civil engineering and 3D mapping (Braun & Clarke, 2006). Three themes emerged: (1) AI applications in 3D mapping and geomatics, (2) the benefits and challenges of AI in civil engineering and infrastructure development, and (3) contextual factors influencing AI adoption within the South African construction and geomatics sectors. Atlas.ti software was used to code, categorise, and analyse the selected literature (Table 2). A total of 50 peer-reviewed studies were included, with findings grouped according to the identified themes.

Table 2: Critical Appraisal Skills Programme Analysis – Frequency and Percentage Findings

Theme	Frequency (N=50)	Percentage
AI in 3D mapping Technologies	34	68%
Impact of AI on Civil Engineering	44	88%
AI Implementation Strategies	29	58%

Source: Developed by the author from themes identified in the reviewed literature

The reviewed literature demonstrates extensive application of AI in 3D mapping technologies, including BIM, digital twins, UAV mapping, and point-cloud processing (Bolton *et al.*, 2021). AI contributes to infrastructure monitoring, defect detection, predictive analytics, and project management (Omar & Nehdi, 2016; Zhang *et al.*, 2020; Chen *et al.*, 2021). However, fewer studies address implementation challenges, including organisational resistance, skills shortages, and interoperability issues (Darko *et al.*, 2020). The CASP analysis identifies the impact of AI on civil engineering as the dominant theme, appearing in 44 studies (88%), followed by AI in 3D mapping technologies in 34 studies (68%), and AI implementation strategies in 29 studies (58%).

Research primarily focuses on digital construction technologies, while organisational, policy, and adoption-related factors remain less explored. The literature also reveals geographical imbalance, with African contexts underrepresented, highlighting the need for further research on AI-enabled 3D geomatics technologies in developing environments. Although the review focused on 2015-2026 literature, foundational studies before 2015 were retained, including Turkan *et al.* (2012), Cheng & Teizer (2013), Kim *et al.* (2013), Volk *et al.* (2014), and LeCun, Bengio and Hinton (2015).

4. Findings and Discussion

4.1 Role of Artificial Intelligence in 3D Mapping Civil Infrastructure

AI-enabled 3D mapping technologies represent a dominant theme in the literature, with 34 of 50 reviewed studies (68%) examining applications within 3D mapping, geomatics, and digital engineering. AI is primarily applied in point-cloud processing, feature extraction, infrastructure inspection, UAV mapping, and integration with BIM and digital twin systems. AI algorithms process large geospatial datasets from laser scanning, LiDAR, and UAV technologies to support object recognition, classification, and infrastructure planning (Ma *et al.*, 2019; Qi *et al.*, 2021). Studies further identify AI applications in defect detection, condition assessment, and maintenance planning, supporting data-driven infrastructure management (Omar & Nehdi, 2016; Zhang *et al.*, 2020; Chen *et al.*, 2021). Integration with BIM and digital twins enhances lifecycle management (Volk *et al.*, 2014; Bolton *et al.*, 2018). However, research remains focused on

technological capabilities, with limited evidence on practical implementation and adoption challenges in developing contexts (Hamledari *et al.*, 2018; Sacks *et al.*, 2020; Javaid *et al.*, 2022).

4.2 impact of artificial intelligence on civil infrastructure delivery

The impact of AI on civil engineering and infrastructure delivery was the most prominent theme, appearing in 44 of the 50 reviewed studies (88%). The reviewed studies indicate that AI supports infrastructure monitoring, condition assessment, defect detection, project management, and predictive infrastructure analytics (Omar & Nehdi, 2016; Ding *et*

al., 2018; Zhang *et al.*, 2020). The literature also highlights the integration of AI within BIM, digital twin environments, and digital construction systems, demonstrating their growing role in infrastructure planning, delivery, and lifecycle management (Volk *et al.*, 2014; Bolton *et al.*, 2018). Overall, the findings associate AI with improved infrastructure monitoring, digital project management, predictive analytics, and integrated digital engineering systems. However, most studies emphasise technological development rather than long-term implementation outcomes and organisational impacts.

4.3 Artificial Intelligence Implementation and Adoption

Most reviewed studies originate from Europe, North America, and East Asia, with few focusing on South Africa of the broader African context. CASP provides a conceptual comparison of AI adoption trends in 3D mapping technologies based on the reviewed literature. The studies indicate that research and implementation of AI-enabled 3D mapping technologies remain concentrated outside Africa (Lu *et al.*, 2020). They also identify skills shortages, interoperability challenges, organisational resistance, a broader digital transformation constraint as key barriers to AI adoption within the construction and engineering sectors (Oesterreich & Teuteberg, 2016; Darko *et al.*, 2020).

4.4 A Conceptual Framework Developed from Themes Identified in the Reviewed Literature

The reviewed literature identified recurring implementation themes, including digital transformation, organisational readiness, skills development, interoperability, BIM integration, and infrastructure management (Oesterreich & Teuteberg, 2016; Darko *et al.*, 2020; Alaloul *et al.*, 2020). Based on these themes, Table 3 presents a conceptual implementation strategy for adopting AI-enabled 3D

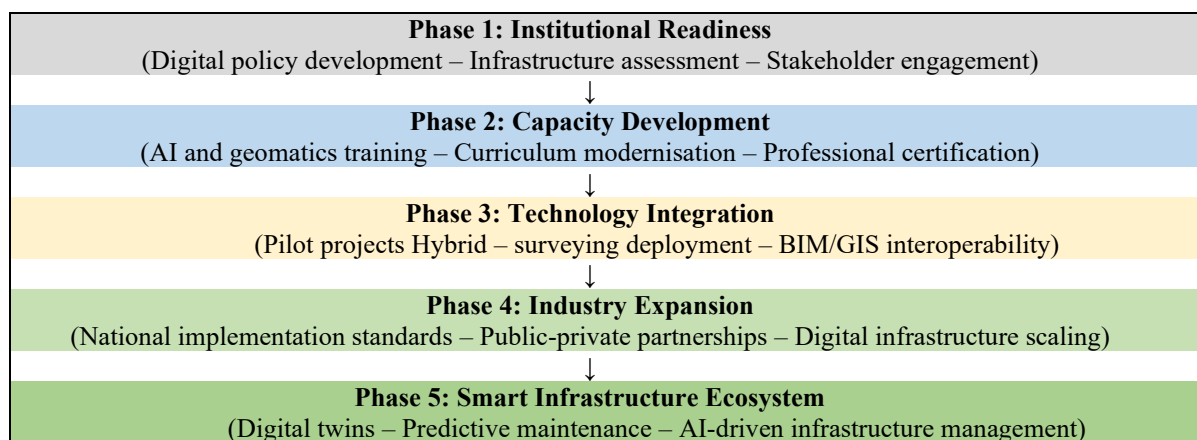
mapping technologies within the South African civil infrastructure sector. The strategy synthesises implementation-related findings from the reviewed literature and serves as a conceptual guide rather than a prescriptive implementation model.

As shown in Table 3, the proposed implementation strategy emphasises organisational readiness and capacity development before large-scale technology deployment. This sequence reflects findings from the reviewed literature, which identify skills shortages, implementation challenges, interoperability constraints, and digital transformation requirements as important considerations for successful AI adoption within the engineering and construction sectors (Oesterreich & Teuteberg, 2016; Darko *et al.*, 2020).

5. Conclusion

This study examined the application of AI-enabled 3D mapping technologies in civil engineering based on a review of existing literature. The findings indicate that AI is primarily applied in automated surveying, spatial data processing, infrastructure monitoring, and engineering decision-making within digital construction environments. The reviewed studies also show that AI is increasingly integrated with technologies such as BIM, digital twins, and geospatial systems to support infrastructure management processes. The literature further highlights that AI adoption in civil engineering is influenced by factors such as technical capability, organisational readiness, and the availability of appropriate digital infrastructure. These factors appear consistently across the reviewed studies as important considerations for implementation. Overall, the study synthesised existing research on AI in 3D mapping and civil infrastructure and identified key application areas and implementation considerations. However, the literature remains

Table 3: Conceptual AI Implementation Strategy for South African Civil Infrastructure Development



Source: Developed by the author from themes identified in the reviewed literature (Oesterreich & Teuteberg, 2016; Alaloul *et al.*, 2020; Darko *et al.*, 2020)

focused on technological development, with limited empirical evidence on large-scale adoption in practice. Further research is recommended to explore real-world

implementation and contextual challenges in developing-country environments.

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