

Leveraging Artificial Intelligence Driven Predictive Analytics for Sustainable Airfield Maintenance: A Project Management Perspective from Air Force Base Waterkloof, South Africa

Mbuyiseni Mdakane¹, Ayodeji Olatunji Aiyetan² and Dillip Kumar Das³

^{1&2}Durban University of Technology, South Africa

³University of KwaZulu-Natal, South Africa

DOI: 10.36108/cbpm/2026.0101

Abstract

Airfield infrastructure in the defence industry is increasingly hindered by outdated facilities, reactive maintenance strategies, and disconnected data management systems, compromising future operational readiness. This paper analyses the main operational challenges related to airfield maintenance in Air Force Base Waterkloof in South Africa, as well as stakeholder readiness to embrace AI-driven predictive analytics. A quantitative survey-based research design was employed with the selected 316 maintenance actors. Data analysis involved descriptive statistics and significance tests. Findings suggest that existing maintenance activities are carried out using an unconnected hybrid strategy, with a focus on reactive maintenance and frequent emergency repairs. Despite certain structural challenges (such as ageing facilities, disconnected databases, and a lack of technical skills), stakeholders showed a high level of readiness to embrace AI predictive analytics. High levels of receptivity were found for machine learning (predictive maintenance and scheduling), computer vision (automatic defect detection), and intelligent decision-making tools that can facilitate the shift to proactive asset management. The study offers actionable insights for construction and project managers by identifying priority areas for adopting AI-driven predictive analytics in maintenance systems. It highlights the need for improved data integration, workforce upskilling, and strategic alignment to facilitate the transition from reactive to predictive maintenance practices in complex, resource-constrained environments.

Keywords: Artificial Intelligence; Airfield Maintenance; Construction Project Management; Infrastructure; Predictive Maintenance.

1 Introduction

Airfield infrastructure is a critical enabler of military readiness, operational safety, and national security. Air Force Base Waterkloof plays a strategic role in supporting both defence operations and government air transport. However, like many legacy infrastructure systems globally, airfields are increasingly challenged by ageing assets, constrained budgets, skills shortages, and growing operational demands. Air transport infrastructure is essential for national economic development and defence capability (Zhang & Graham, 2020; Kölker, Stoebke & Lütjens, 2025). Traditionally, airfield maintenance has been undertaken using reactive or time-based methods, leading to inefficiency. Studies in infrastructure and asset management have consistently highlighted that reactive maintenance practices lead to suboptimal performance and increased long-term expenditure (Al-Turki, 2011; Mobley, 2002). Pavement surfaces, lighting systems, and navigation aids play an important role in the aviation industry when maintained. In addition, the lack of information management and data integration makes it difficult for project managers to manage their resources efficiently (Love et al., 2016). Over the last few years, AI has become an innovative

solution for infrastructure management (predictive analytics, anomaly detection) and a decision-making tool.

AI-based maintenance management utilises both past and real-time information to anticipate potential breakdowns, optimise maintenance scheduling, and increase the effectiveness of the assets (Zonta et al., 2020). Research indicates that the application of AI leads to greater forecasting efficiency and better results in the field of construction and project management (Pan and Zhang, 2021). The introduction of AI-driven predictive analytics solutions in maintenance is associated with various technological shortcomings. Organisational preparedness, technological readiness, staff expertise, and other aspects affect the implementation of new technologies (Oesterreich and Teuteberg, 2016). The use of AI is influenced by various restrictions in a military context due to data privacy and confidentiality. This study investigated the role of AI-driven predictive analytics in addressing airfield maintenance challenges within the specific context of Air Force Base Waterkloof in Gauteng Province, South Africa. This survey-based research was informed by literature and case evidence. The study explores managerial, technical, organisational,

¹ Corresponding Author

Email address: Sokemdakane@gmail.com

and project-related drivers affecting maintenance outcomes. Focus is specifically placed on aspects like the state of assets, budget limitations, skill sets, and technology readiness. Connectivity of an airport is influenced by passenger routes and destination airports (Kölker, Stoebe, and Lütjens, 2025). These results are expected to advance theory and practice by contributing to understanding the use of AI for prediction, planning, and decision-making in such an environment. For project/construction managers, the study offers a contextualised understanding of how AI-driven predictive analytics adoption strategies can be prioritised to address maintenance challenges. The research also contributes to digital transformation in infrastructure management, within resource-constrained and security-sensitive settings.

2 Literature Review

2.1 Traditional Airfield Maintenance Challenges and Operational Constraints

Airfield infrastructure, comprising pavement networks, lighting systems, and navigation aids, demands continuous operational reliability and strict adherence to safety regulations. However, airfields in developing nations face severe structural constraints, including ageing assets, chronic budgetary limits, and technical skill shortages. Historically, airfield asset management has relied on reactive and time-based maintenance practices, which are widely recognised as inefficient and ineffective at preventing sudden operational failures (Al-Turki, 2011; Love et al., 2016).

Managing complex airfield infrastructure requires robust scheduling, integrated governance, and accurate data collection. Inadequate planning and decision-making lead to compounding lifecycle costs and asset degradation (Love et al., 2016). Furthermore, an inability to collect high-quality operational data restricts asset management optimisation, locking facilities into purely reactive operational cycles (Ucar, Karakose & Kırımça, 2024). Beyond technical barriers, organisational capacity plays a pivotal role in maintenance efficiency. Transitioning to intelligent asset management requires both technical competence and organisational digital readiness; however, widespread skill shortages continue to impede the adoption of Industry 4.0 technologies in infrastructure management (Oesterreich & Teuteberg, 2016).

2.2 Shift Toward Intelligent Maintenance and AI-Driven Subfields

To overcome the limitations of legacy corrective strategies, maintenance practices are undergoing a paradigm shift toward condition-based and predictive maintenance. Predictive maintenance relies on data analytics to foresee asset failure and optimise maintenance interventions prior to functional breakdown, thereby enhancing resource efficiency and operational decision-making.

Artificial Intelligence (AI) serves as the primary engine driving this transition, enabling the processing of complex, multi-source datasets—such as real-time sensor streams, Non-Destructive Testing (NDT) structural evaluations, and mechanistic pavement stress data (Gkyrtis, Plati & Loizos, 2022, 2025; Madhukar, 2024). Modern literature highlights that incorporating AI into predictive analytics substantially improves the accuracy, effectiveness, and reliability of infrastructure management systems (Ucar et al., 2024). Rather than applying AI as an overarching concept, digital transformation in infrastructure relies on specific AI subfields:

- **Machine Learning & Deep Learning:** Applied to evaluate structural health, identify anomalous degradation patterns, and perform predictive failure modelling across critical transport networks (Bris-Peñalver, Verdecia-Peña & Alonso, 2026; Plevris & Papazafeiropoulos, 2024; Savaş, 2025).
- **Computer Vision Systems:** Utilised via camera-based object and defect detection to identify surface anomalies, pavement cracking, and runway foreign object debris (FOD) with greater speed and precision than manual inspection (Priyadharsini, Jagatheesaperumal, Alkhamees & Hassan, 2025).
- **Integrated CMMS and Life-Cycle Cost Frameworks:** Leveraging Computerised Maintenance Management Systems alongside Life Cycle Cost Analysis (LCCA) allows managers to evaluate Net Present Values (NPV) and select optimal long-term economic interventions (Orabi & Shatila, 2025).

2.3 Data Integration and Cross-Domain Governance

Achieving sustainable infrastructure performance requires moving away from siloed departmental approaches toward integrated, cross-domain maintenance architectures (Lahna, Kamsu-Foguem & Abanda, 2023). Integrating fragmented data systems—such as linking real-time Computer Vision defect logs and sensor streams with CMMS databases—provides a unified spatial overview of asset condition. This holistic data integration is essential for supporting intelligent decision-support tools and maximising long-term asset resilience across complex transport networks (Bris-Peñalver et al., 2026; Lahna et al., 2023).

2.4 Research Gap and Contextual Novelty

While the global literature establishes a clear shift toward data-driven, intelligent maintenance strategies, significant empirical gaps remain:

1. **Defence Sector Infrastructure Decline:** In South Africa, broader defence capability and planning frameworks have experienced severe long-term decline and budgetary pressure (Gopaul, Van der Lingen & Oosthuizen, 2024; Louw & Esterhuysen, 2022). Strategically vital installations like Air

Force Base Waterkloof operate under persistent budget constraints and severe operational strain, yet research on digital transformation in these environments is minimal.

2. **Contextual & Security Gap:** Deploying AI-driven predictive analytics in security-sensitive military settings raises unique challenges regarding data confidentiality, security governance, and institutional readiness. Existing predictive maintenance models are predominantly tailored to commercial airports in high-income economies, leaving a distinct gap regarding military airfields in developing African contexts.

This study fills this empirical gap by adopting a project management perspective to evaluate the operational factors influencing airfield maintenance at Air Force Base Waterkloof and to assess stakeholder readiness to adopt AI-driven predictive analytics within complex, security-sensitive infrastructure systems.

3 Research Methodology

This study adopts a quantitative, cross-sectional survey design to investigate the factors influencing airfield maintenance performance and to evaluate the perceived role of AI-driven predictive analytics in improving maintenance practices at Air Force Base Waterkloof, South Africa. The methodological approach is grounded in a prior review of the literature and case-based evidence, which informed the identification of key constructs and variables examined in the study.

3.1 Data Collection

A survey approach was adopted to collect data from the airfield workers/participants. Due to the cross-sectional nature of this study, the data were used to assess the current state of affairs. The questionnaire covered demographics, maintenance strategies, maintenance challenges, current operational activities, and AI-enabled maintenance operations. A five-point Likert scale was used for collecting the responses. The instrument consisted of closed-ended questions organised into themes such as demographic variables, types of maintenance strategies, maintenance problems, current maintenance activities, and the use of AI-driven predictive analytics in maintenance activities. The responses were captured using a scale from 1 (strongly disagree) to 5 (strongly agree), thus capturing opinions. Only people with airfield experience participated. Participation was voluntary, and respondents were informed of the study's purpose, anonymity, and confidentiality. Due to the sensitive military context, no classified or operationally restricted information was collected.

A questionnaire survey was conducted among 316 airfield participants at Air Force Base Waterkloof to collect data. The respondents comprised General

Workers, Artisans, Civil Technicians, Electrical Technologists, Civil Engineers, Project Managers, Facility Managers, Environmentalists, and Runway Management personnel. The data collection process ensured that the sample adequately reflected the operational workforce responsible for maintenance activities, thereby enhancing the practical relevance of the findings. The questionnaire was formulated based on the constructs identified in the literature review and aligned with the study's objective and variables, such as maintenance operations and Artificial Intelligence.

3.2 Data Analysis

A combination of descriptive and inferential statistical techniques was used to address the research objectives. Descriptive statistics were used to summarise the respondents' demographic characteristics and perceptions regarding maintenance strategies, operational activities, maintenance challenges, and AI-enabled maintenance practices. These included frequencies, percentages, means, and standard deviations. To determine whether the observed response distribution differed significantly from the expected distribution, chi-square goodness-of-fit tests were performed for each questionnaire item. The chi-square goodness-of-fit test examined whether the frequencies of responses across the five-point Likert scale differed significantly from the expected frequencies under the null hypothesis. Statistical significance was evaluated using two-tailed p -values at the 5% level ($p < 0.05$). The combined use of descriptive and inferential statistics enabled the identification of dominant maintenance practices, operational challenges, and stakeholder perceptions regarding the adoption of AI-driven predictive analytics.

This further helps in making sure that the results and conclusions arrived at are accurate and representative of the population under investigation. Analysis helped identify the dominant maintenance types and current maintenance activities practised, their relative prevalence, key operational and organisational challenges affecting maintenance performance, and the perceived effectiveness of AI-driven predictive analytics applications in improving maintenance activities. Analyses were conducted in a structured, systematic manner to ensure consistency and accuracy. The integration of descriptive and inferential methods provided both exploratory insights and empirical validation, supporting a comprehensive interpretation of the data in the context of airfield maintenance and AI adoption.

4. Findings and Discussion

4.1 Respondents Profile

The respondent profile provides essential context for interpreting the study's findings, particularly regarding the operational activities of airfield maintenance at Air

Force Base Waterkloof. Table 1a and 1b present the respondents' profile. The sample is predominantly male (84.2%), with females comprising only 15.8%. Utete (2021) observed that understanding the gender profile of technical and operational staff was essential for workforce diversity and planning targeted capacity-building interventions. This reflects the traditionally male-dominated nature of technical and military maintenance environments. While expected, this imbalance constrains the diversity of perspectives, particularly on technology adoption and organisational practices, and may limit the generalisability of perceptual findings across a more gender-balanced workforce. Age distribution indicates a largely mid-career cohort.

A majority of the respondents range between 31-40

Table 1a: Profile of Respondents

Attributes	Frequency	Percentage
Gender		
Male	266	84.2%
Female	50	15.8%
Total	316	100.00
Age Group in Years		
18–24	0	0
25–30	27	8.6%
31–40	151	47.8%
41–50	93	29.4%
50–60	45	14.2%
Total	316	100.00
Education Level		
Sec Grades	65	20.6%
Matric	180	57.0%
Diploma	40	12.7%
Postgrad Dipl	15	4.7%
B-Tech	10	3.2%
BEng Degree	6	1.9%
Total	316	100

years (47.8%) and 41-50 years (29.4%), implying that over three-quarters of the respondents are within the age group of 31-50 years. There were no respondents aged below 25 years, while only 8.6% were aged between 25 and 30 years. It shows a relatively experienced workforce but a lack of participation by young professionals. This may have an impact on the results since younger individuals are more receptive to innovations such as AI. Nevertheless, the dominance of experienced individuals ensures that the findings are based on practical knowledge. In terms of educational level, the workforce is mostly skills-based. A large

percentage of the respondents have completed secondary education (matriculation), at 57.0%, while very few individuals have advanced degrees.

This may affect the extent of familiarity with complex theories and frameworks, but also ensures that the answers are based on experience and practical knowledge. Professionally, the respondents belong to the operations department, with artisans being the most dominant group (51.58%), followed by general workers (25.64%), and technicians (14.87%). The number of respondents is not large within the engineering and management cadre. The level of experience is quite high, as 61.0% have between 17 and 25 years of experience. This increases the dependability of evaluation since the knowledge gained is substantial,

Table 1b: Profile of Respondents

Attributes	Frequency	Percentage
Professional Role1		
Gen/Workers	81	25,64%
Artisans	163	51,58%
Technicians	47	14,87%
Technologists	10	3,16%
Pr Consultants	5	1,58%
Engineering	6	1,90%
Management	4	1,27%
Total	316	100
Experience (Years)		
4–6 years	7	2.2%
7–10 years	12	3.8%
11–13 years	18	5.7%
14–16 years	42	13.3%
17–20 years	99	31.3%
21–25 years	94	29.7%
26–30 years	43	13.6%
Above 30 years	1	0.3%
Total		100

but it could lead to bias against new innovations and processes. Despite limitations, gender imbalance, limited youth representation, and fewer highly educated or managerial respondents, its strengths lie in operational expertise and experience. Thus, the sample is appropriate for the study's objectives, as in applied infrastructure research, functional relevance outweighs strict demographic balance.

4.2 Maintenance Activities (Current Practice)

Table 2 presents the distribution of respondents' perceptions regarding the maintenance strategies

Table 2: Types of Maintenance

Maintenance Type	Mean	SD	p-value	Remarks
Preventive Maintenance	3.95	0.82	0.024	Maintenance Strategy Analysis
Reactive Maintenance	3.96	0.80	0.005	Maintenance Strategy Analysis
Predictive Maintenance	3.92	0.83	0.003	Advanced Maintenance Practices
Corrective Maintenance	3.94	0.81	0.042	Maintenance Operations Review
Condition-Based Maintenance	3.97	0.79	0.015	Technology-Driven Maintenance

currently employed at Air Force Base Waterkloof. Descriptive statistics indicate a relatively uniform prevalence across all maintenance strategies, with mean scores ranging narrowly from 3.92 to 3.97. Condition-based maintenance (Mean = 3.97, SD = 0.79) and reactive maintenance (Mean = 3.96, SD = 0.80) recorded the highest average ratings, followed closely by preventive maintenance (Mean = 3.95) and corrective maintenance (Mean = 3.94). The similarity in these mean scores suggests that no single maintenance strategy is consistently prioritised, reflecting a hybrid maintenance approach rather than a clearly defined strategic maintenance framework. Ideally, maintenance management should emphasise proactive and predictive maintenance strategies over reactive interventions.

The continued prominence of reactive maintenance suggests that maintenance activities remain largely failure-driven, with corrective actions frequently initiated only after equipment or infrastructure failures occur. The relatively low standard deviations (0.79–0.83) indicate a high level of consistency in respondents' perceptions across all maintenance strategies. The chi-square goodness-of-fit test showed that the distribution of responses for each maintenance strategy differed significantly from the expected distribution ($p < 0.05$), indicating that respondents exhibited clear patterns of agreement rather than randomly distributed opinions. In particular, the significant result for predictive maintenance ($p = 0.003$) reflects a strong recognition of its importance as a modern maintenance approach. Overall, the findings suggest that Air Force Base Waterkloof is operating within a transitional maintenance environment in which legacy reactive practices coexist with emerging technology-driven maintenance strategies, although

full integration of predictive maintenance has yet to be achieved.

Table 3 shows that maintenance activities at Air Force Base Waterkloof are predominantly reactive. Emergency repairs (Mean = 4.18, SD = 0.58) and runway inspections (Mean = 4.12, SD = 0.77) recorded the highest ratings, reflecting a strong emphasis on immediate operational readiness. The prominence of emergency repairs supports the findings in Table 2, confirming continued reliance on reactive maintenance, which is likely to increase lifecycle costs through unplanned repairs.

Routine maintenance of pavements (Mean = 4.09) and drainage systems (Mean = 4.10) was also rated highly, whereas lighting maintenance (Mean = 3.82) and equipment servicing (Mean = 3.80) received comparatively lower ratings, suggesting potential weaknesses in auxiliary systems. The chi-square goodness-of-fit test indicated that the response distributions for all maintenance activities differed significantly from the expected distribution ($p < 0.05$), demonstrating consistent respondent perceptions. Overall, the findings suggest that maintenance remains largely reactive despite regular execution of routine activities.

4.3 Challenges of Maintenance

Table 4 indicates that the principal constraints affecting maintenance performance are ageing infrastructure (Mean = 4.12, SD = 0.77) and a reactive maintenance culture (Mean = 4.11, SD = 0.73), highlighting asset deterioration and reactive practices as major barriers to effective maintenance planning. Fragmented data systems (Mean = 3.85, SD = 0.83) and technical skills shortages (Mean = 3.84, SD = 0.82) further constrain decision-making and the transition to predictive maintenance. Equipment downtime (Mean = 3.71, SD

Table 3: Maintenance Activities (Current Practice)

Maintenance Activity	Mean	SD	p-value	Remarks
Runway Inspections	4.12	0.77	0.006	Routine Maintenance Activities
Pavement Repairs	4.09	0.74	0.013	Maintenance Operations
Lighting Maintenance	3.82	0.86	0.022	Electrical Systems Maintenance
Drainage Maintenance	4.10	0.75	0.033	Infrastructure Support Systems
Emergency Repairs	4.18	0.584	0.004	Reactive Maintenance Activities
Equipment Servicing	3.80	0.87	0.047	Equipment Maintenance

Table 4: Challenges of Maintenance

Maintenance Challenge	Mean	SD	p-value	Remarks
Ageing Infrastructure	4.12	0.77	0.002	Infrastructure Constraints Analysis
Budget Constraints	3.81	0.85	0.009	Resource Constraints Analysis
Skills Shortage	3.84	0.82	0.018	Workforce Capacity Analysis
Reactive Maintenance Culture	4.11	0.73	0.004	Maintenance Strategy Gaps
Fragmented Data Systems	3.85	0.83	0.003	Data Management Challenges
Equipment Downtime	3.71	0.92	0.029	Operational Efficiency Analysis

= 0.92) received the lowest rating, with greater variation in responses across operational units. The chi-square goodness-of-fit test showed that the response distributions for all maintenance challenges differed significantly from the expected distribution ($p < 0.05$), indicating broad agreement that these are the key structural, organisational, and technological constraints affecting maintenance performance.

4.4 Perspectives of AI-Enabled Maintenance Activities

Table 5 presents stakeholders' perceptions of integrating Artificial Intelligence into airfield asset management. Overall, respondents expressed strong support for AI-enabled maintenance practices. Automated inspections (Mean = 4.11, SD = 0.73), decision support systems (Mean = 4.10, SD = 0.75), and predictive maintenance (Mean = 4.09, SD = 0.74) received the highest ratings, reflecting confidence in

lifecycle costs and reduces asset reliability (Mobley, 2002; Muchiri et al., 2011; Swanson, 2001; Wireman, 2004).

The findings further identify ageing infrastructure (Mean = 4.12), a reactive maintenance culture (Mean = 4.11), fragmented data systems (Mean = 3.85), and technical skills shortages (Mean = 3.84) as the principal barriers to effective maintenance management. These challenges support previous research highlighting that fragmented information systems constrain predictive maintenance and informed decision-making (Lahna et al., 2023; Ucar et al., 2024).

Despite these operational constraints, the chi-square goodness-of-fit test indicated that respondents consistently expressed positive perceptions of AI-enabled maintenance activities ($p < 0.05$). Automated inspections (Mean = 4.11), decision support systems

Table 5: AI-Enabled Maintenance Activities

AI-Enabled Activity	Mean	SD	p-value	Remarks
Predictive Maintenance	4.09	0.74	0.001	AI in Maintenance Optimisation
Automated Inspections	4.11	0.73	0.004	AI-Based Inspection Systems
Fault Detection	3.95	0.82	0.003	Intelligent Fault Detection
Scheduling Optimisation	3.96	0.80	0.002	AI for Planning Efficiency
Resource Optimisation	3.79	0.88	0.010	Resource Management AI
Data Integration (Digital Twin)	3.85	0.83	0.001	Data-Driven Decision-Making
Decision Support	4.10	0.75	0.002	AI for Strategic Decisions

AI's ability to improve maintenance planning, detect defects early, and reduce unplanned downtime.

AI-driven scheduling optimisation (Mean = 3.96) and fault detection (Mean = 3.95) were also rated positively, while data integration through Digital Twins (Mean = 3.85) and resource optimisation (Mean = 3.79, SD = 0.88) received comparatively lower, but favourable, ratings. The higher variation in resource optimisation suggests differing levels of technical familiarity among respondents. The chi-square goodness-of-fit test indicated that the response distributions for all AI-enabled maintenance activities differed significantly from the expected distribution ($p \leq 0.01$), demonstrating broad agreement on the potential of AI to enhance maintenance performance and address existing operational challenges.

4.5 Synthesis and Critical Discussion

Evaluating the findings across Tables 2–5 indicates that airfield maintenance at Air Force Base Waterkloof operates within a hybrid maintenance framework that remains largely reactive. Although condition-based maintenance received the highest rating (Mean = 3.97), the similarly high ratings for reactive maintenance (Mean = 3.96) and emergency repairs (Mean = 4.18) suggest that maintenance activities continue to be driven by equipment failures rather than proactive planning. This finding is consistent with previous studies showing that reactive maintenance increases

(Mean = 4.10), and predictive maintenance (Mean = 4.09) received the strongest support, suggesting that the principal barrier to AI adoption is not stakeholder acceptance but organisational readiness, integrated data systems, and workforce capacity building (Bris-Peñalver et al., 2026; Jardine et al., 2006; Madhukar, 2024; Savaş, 2025). Bridging this implementation gap is essential for improving operational reliability and achieving sustainable airfield maintenance.

5 Conclusion, Contributions, and Further Research

5.1 Synthesis of Findings

This paper explores the factors influencing the performance of maintenance activities in Air Force Base Waterkloof. It measures stakeholders' perceptions of the use of AI to transform asset operations. Evidence shows that the current maintenance environment at Air Force Base Waterkloof is characterised by a transitional maintenance regime that adopts a hybrid approach, using both reactive and condition-based methods, with emergency maintenance taking precedence over planning. Architectural limitations in the form of ageing infrastructure, data silos, and a lack of technical competencies make up the core barriers in this operation. At the same time, operational stakeholders have displayed very high levels of receptiveness to various forms of AI technologies such as predictive

analytics, computer vision, and intelligent decision-support systems.

5.2 Contributions to Knowledge

Theoretical Contributions: This research contributes to the body of literature on infrastructure asset management and digital transformation in defence environments through the development of a socio-technological model of the 'Implementation Gap'. The existing literature has attributed the slow adoption of 4IR technology in military and public sector organisations to user resistance and technophobia. This research proves that the operational staff members of military organisations accept the need for transformative technologies like AI.

The critical theoretical contribution of this research is that the key barrier to digital transformation in high-security defence infrastructure is organisational-architectural in nature rather than user resistance: operational readiness is hindered not by user unwillingness but by a lack of integrated data models and data silos.

Practical and Operational Implications: The research provides a tangible blueprint for the shift from failure-based repair to proactive asset management for airfield managers, defence engineers, and facility operators. Importantly, the research shows that the use of AI through the implementation of standalone predictive algorithms over isolated systems fails because of data silos.

In order to overcome this issue, an enterprise Digital Twin architecture is required for operationalising AI technologies. Digital Twin is an architecture that acts as an integration layer by combining all data silos into one three-dimensional digital representation of the asset, such as Pavement Condition Indices (PCI) results from computer-vision-based automated inspection of the airfield, wheel load information from the structural data of past incidents, meteorological analysis, and Computerised Maintenance Management System (CMMS) data. Integration of those operational data silos into the data streams allows Machine Learning algorithms to implement failure prediction models in interdependent airfield sub-systems (such as pavement, drainage, and airfield lighting). Thus, the infrastructure managers get a detailed step-by-step blueprint on how

to eliminate data silos before implementing any large-scale predictive models.

Social, Policy and Governance Implications: At the societal level and from a policy perspective, the modernisation of military infrastructure affects national security readiness and strategic air mobility capabilities, as well as the effective management of public capital assets. The research provides evidence-based guidelines for military procurement policies, recommending institutional frameworks to focus on 4IR compliance of infrastructure standards, cybersecurity issues, and capacity building. Alignment of the South African military airfield management with digital twin and AI standards will increase its tactical capabilities while ensuring a sustainable infrastructural base in the long run.

5.3 Limitations and Future Research

There are some limitations in this research. The data set is based mostly on cross-sectional survey data from the operational and technical personnel rather than executive policymakers. Data collection has been restricted by the security classification of the military, thus restricting access to real-time telemetry and confidential asset degradation records.

The further scope of research includes:

- Longitudinal empirical studies measuring the changes in post-implementation metrics such as MTBF, maintenance cycle times, and lifecycle cost reduction after pilot deployment of Digital Twin or AI.
- Integrating real-world sensor telemetry and CMMS log data along with managerial interviews to enrich the data triangulation.
- Development of policy and governance frameworks such as institutional governance, specialised defence procurement processes, data ownership, and cybersecurity requirements for management of digital twins of strategic military assets.

References

- Al-Turki, U. (2011). A framework for strategic planning in maintenance. *Journal of Quality in Maintenance Engineering*, 17(2), 150–162.
- Bris-Peñalver, F. J., Verdecia-Peña, R., & Alonso, J. I. (2026). A survey of AI-enabled predictive maintenance for railway infrastructure: Models, data sources, and research challenges. *Sensors*, 26(3), 906. <https://doi.org/10.3390/s26030906>

- Gkyrtis, K.; Plati, C.; Loizos, A. (2022). Mechanistic Analysis of Asphalt Pavements in Support of Pavement Preservation Decision-Making. *Infrastructures*, 7, 61.
- Gkyrtis, K., Plati, C., & Loizos, A. (2025). A step toward improving management practices for airfield pavement infrastructures: a mechanistic-based analysis approach. *Structure and Infrastructure Engineering*, 21(5), 787–798.
- Gopaul, K., Van der Lingen, E., & Oosthuizen, R. (2024). Reflecting on the rise and decline of the South African Defence Industry.
- Jardine, A. K. S., Lin, D., & Banjevic, D. (2006). A review on machinery diagnostics and prognostics implementing condition-based maintenance. *Mechanical Systems and Signal Processing*, 20(7), 1483–1510. <https://doi.org/10.1016/j.ymssp.2005.09.012>
- Kölker, K., Stoebe, E., & Lütjens, K. (2025). In the flow of connectivity: A dynamic network analysis of Europe's air transportation system—*Journal of the Air Transport Research Society*, 4, 100055.
- Lahna, T., Kamsu-Foguem, B., & Abanda, H. F. (2023). Maintenance in airport infrastructure: A bibliometric analysis and future research directions. *Journal of Building Engineering*, 76, 106876.
- Louw, C. R. G. M., & Esterhuysen, A. (2022). South African defence decision-making: analysing dysfunctional approaches. *Defence & Security Analysis*, 38(4), 389–409.
- Love, P. E. D., Edwards, D. J., & Smith, J. (2016). Rework causation: Emergent theoretical insights and implications for research. *Journal of Construction Engineering and Management*, 142(6). [https://doi.org/10.1061/\(ASCE\)CO.1943-7862.0001111](https://doi.org/10.1061/(ASCE)CO.1943-7862.0001111)
- Madhukar, D. (2024). AI-driven predictive maintenance in data infrastructure: A multi-modal framework for enhanced system reliability. *International Journal of Scientific Research in Computer Science, Engineering and Information Technology*, 10(6), 824–834. <https://doi.org/10.32628/CSEIT241061118>
- Mobley, R. K. (2002). *An introduction to predictive maintenance* (2nd ed.). Butterworth-Heinemann.
- Muchiri, P., Pintelon, L., Gelders, L., & Martin, H. (2011). Development of maintenance function performance measurement framework and indicators. *International Journal of Production Economics*, 131(1), 295–302. <https://doi.org/10.1016/j.ijpe.2010.04.039>
- Orabi, J., & Shatila, W. (2025). Impact of Life Cycle Cost of Airfield Pavement on Airport Operations. In *Big Data in Finance: Transforming the Financial Landscape: Volume 1* (pp. 25–41). Cham: Springer Nature Switzerland.
- Oesterreich, T. D., & Teuteberg, F. (2016). Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Computers in Industry*, 83, 121–139. <https://doi.org/10.1016/j.compind.2016.09.006>
- Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, 122, 103517. <https://doi.org/10.1016/j.autcon.2020.103517>
- Plevris, V., & Papazafeiropoulos, G. (2024). AI in Structural Health Monitoring for Infrastructure Maintenance and Safety. *Infrastructures*, 9(12), 225. <https://doi.org/10.3390/infrastructures9120225>
- Priyadharsini, S., Jagatheesaperumal, S. K., Alkhamees, B. F., & Hassan, M. M. (2025). Foreign object debris detection in lane images using deep learning methodology: *PeerJ Computer Science*, 11, e2570.
- Savaş, S. (2025). Artificial intelligence in construction project management: Trends, challenges and future directions. *Journal of Design for Resilience in Architecture and Planning*, 6(2), 221–238. <https://doi.org/10.47818/DRArch.2025.v6i2165>
- Swanson, L. (2001). Linking maintenance strategies to performance. *International Journal of Production Economics*, 70(3), 237–244. [https://doi.org/10.1016/S0925-5273\(00\)00067-0](https://doi.org/10.1016/S0925-5273(00)00067-0)
- Ucar, A., Karakose, M., & Kırımça, N. (2024). Artificial intelligence for predictive maintenance applications: Key components, trustworthiness, and future trends. *Applied Sciences*, 14(2), 898. <https://doi.org/10.3390/app14020898>

- Utete, R. (2021). Capacity building as a strategic tool for employment equity implementation in the financial sector. *SA Journal of Human Resource Management*, 19, 10.
- Wireman, T. (2004). *Total productive maintenance*. Industrial Press.
- Zhang, F., & Graham, D. J. (2020). Air transport and economic growth: a review of the impact mechanism and causal relationships. *Transport Reviews*, 40(4), 506–528. <https://doi.org/10.1080/01441647.2020.1738587>
- Zonta, T., Da Costa, C. A., Da Rosa Righi, R., De Lima, M. J., Da Trindade, E. S., & Li, G. P. (2020). Predictive maintenance in the Industry 4.0: A systematic literature review. *Computers & Industrial Engineering*, 150, 106889. <https://doi.org/10.1016/j.cie.2020.106889>