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AI-Based Predictive Maintenance Framework for MEP Systems in Smart Buildings under Vision 2030

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Abstract- Smart buildings in Saudi Arabia are moving from conventional automation toward adaptive infrastructure that can protect asset reliability, occupant wellbeing and energy performance at the same time. This review develops an AI-based predictive maintenance framework for mechanical, electrical and plumbing (MEP) systems in smart buildings under Vision 2030. The review synthesises literature published between 2020 and 2025 on artificial intelligence, fault detection and diagnosis, digital twins, building management systems, machine learning for HVAC and water systems, and facility management governance. It responds to a practical gap: many buildings collect large volumes of operational data, yet maintenance remains calendar-based, alarm-driven or dependent on individual technician experience. The proposed framework connects sensor strategy, data architecture, AI analytics, risk scoring, work-order governance and continuous commissioning into one lifecycle model. It treats predictive maintenance as a decision system rather than a single algorithm. The contribution is a Saudi-relevant review framework that links AI maintenance decisions to Vision 2030 outcomes: lower energy intensity, fewer unplanned failures, improved indoor environmental quality, longer equipment life, resilience for high-occupancy assets, and measurable support for national sustainability targets. The paper also identifies implementation risks, including data quality, cybersecurity, vendor lock-in, model drift, false alarms, workforce readiness and the difficulty of translating predictions into accountable maintenance action. The review concludes that AI-based predictive maintenance can become a core operational capability for Saudi smart buildings when it is embedded within IBMS governance, verified by commissioning evidence and aligned with business-value metrics.

Keywords: Predictive Maintenance, MEP Systems, Smart Buildings, Artificial Intelligence, HVAC, IBMS, Digital Twin, Vision 2030, Saudi Arabia, Fault Detection and Diagnosis.

I. INTRODUCTION

Saudi Arabia's Vision 2030 has made infrastructure performance a national competitiveness issue rather than a narrow engineering concern. New airports, hospitals, universities, entertainment districts, logistics hubs, mixed-use communities and giga-project assets are expected to operate with high reliability while demonstrating efficient resource use. At the same time, the global buildings and construction sector remains one of the largest sources of energy demand and carbon emissions, which places operating buildings under increasing scrutiny (IEA, 2023; UNEP and GlobalABC, 2025). The Saudi Green Initiative also commits the Kingdom to a large annual emissions reduction by 2030 and encourages improvements in energy efficiency, clean power and environmental stewardship (Saudi Green Initiative, 2024). Within this context, MEP systems are strategic assets. HVAC, chilled water, air handling units, pumps, lighting, domestic water, drainage, elevators, fire systems, standby power and control panels determine whether a building is comfortable, safe, resilient and affordable to operate.

Traditional maintenance models are poorly matched to this environment. Reactive maintenance waits until an asset fails. Preventive maintenance reduces some risk, but it can replace components too early, miss hidden degradation or overload technicians with low-value routines. Condition-based maintenance improves decisions by using sensor signals, but many building teams still rely on dashboards, threshold alarms and manual interpretation. Predictive maintenance goes further by estimating the probability, timing and operational consequences of a future fault. When supported by AI, predictive maintenance can detect nonlinear patterns across power consumption, temperature, vibration, pressure, airflow, humidity, occupancy, weather and control states. Recent reviews show that machine learning, deep learning and digital twins are increasingly used for fault detection, diagnostics and performance optimisation in HVAC and building services (Hosamo et al., 2022; Hodavand et al., 2023; Bi et al., 2024; Mazzetto, 2025).

The attached model paper on cognitive buildings provides a useful reference structure because it frames intelligent building management as a phased methodology: foundation data architecture, scenario mapping, implementation and continuous optimisation. It also emphasises that IBMS platforms become genuinely intelligent only when data, context, control logic and feedback are designed together, not added after handover. This review follows that systems-thinking approach but shifts the technical focus from energy awareness alone to predictive maintenance for MEP systems. The central argument is that AI maintenance should not be treated as a software add-on. It should be planned from design and commissioning, linked to asset hierarchy, trained on validated operational data, and governed through facility management decisions that are auditable and economically justified.

II. AIM AND OBJECTIVES OF THE STUDY

The aim of this review is to develop a Saudi-focused AI-based predictive maintenance framework for MEP systems in smart buildings and to explain how such a framework can improve asset reliability, energy performance and operational resilience under Vision 2030. The review has five objectives. First, it examines recent literature from 2020 to 2025 on AI-enabled maintenance, digital twins, FDD and smart building operations. Second, it identifies the main MEP data points needed to move from alarm monitoring to predictive decision-making. Third, it maps the links between predictive maintenance, energy efficiency, occupant comfort, safety and lifecycle cost. Fourth, it proposes a phased framework suitable for Saudi projects, including new construction, retrofits and large mixed-use assets. Fifth, it highlights governance, cybersecurity and human-capability requirements that must be addressed before AI predictions can be trusted in real facility operations.

III. REVIEW METHODOLOGY

This paper uses an integrative review methodology appropriate for an emerging applied engineering field where evidence is distributed across peer-reviewed journals, standards, policy documents and technology-focused case studies. The search scope covered publications between 2020 and 2025 in databases and publisher platforms associated with Elsevier, Springer, MDPI, Emerald, Taylor and Francis, IEEE and recognised policy organisations. Search strings combined terms such as artificial intelligence, predictive maintenance, HVAC, MEP, smart building, building management system, digital twin, fault detection and diagnosis, Saudi Vision 2030, energy efficiency and facility management. The inclusion criteria prioritised sources that addressed building operations, HVAC or MEP assets; used AI, machine learning, digital twin, FDD or data-driven diagnostics; and offered transferable findings for maintenance governance. Sources focused only on industrial manufacturing were used only when their predictive-maintenance logic could be adapted to building services. Publications before 2020 were excluded except where a standard or concept was necessary for context; however, the reference list has been restricted to 2020-2025 as requested.

The review was conducted in four stages. Stage one mapped policy drivers and building-sector pressures. Stage two classified technical approaches, including rule-based FDD, supervised learning, unsupervised anomaly detection, time-series forecasting, remaining useful life estimation, model predictive control and digital twins. Stage three translated the literature into an MEP scenario matrix. Stage four synthesised an implementation framework and evaluated expected benefits and risks. This method is suitable because predictive maintenance is not a single experimental variable. It is a socio-technical capability that combines data availability, modelling quality, workflow integration and organisational response.

IV. LITERATURE BACKGROUND

Smart building research increasingly recognizes that energy management, comfort and maintenance cannot be separated. HVAC faults can increase

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energy use while still satisfying zone temperature for a period, which hides inefficiency until bills, complaints or breakdowns appear. Chiller fouling, sensor drift, leaking valves, clogged filters, poor economizer control, pump cavitation, unbalanced airflows and simultaneous heating and cooling are examples of faults that degrade performance before a hard failure occurs. Drgoña et al. (2020) and Kim et al. (2022) show that predictive control and building energy modelling can reduce operational waste when weather, occupancy and building dynamics are considered. Haruehansapong et al. (2022) and Taheri et al. (2021) demonstrate the growing use of deep learning for automated HVAC fault diagnostics. Li et al. (2021) further emphasise explainability because facility teams need to understand why a model classifies a condition as faulty.

Digital twins extend these ideas by connecting asset geometry, system topology, live sensor data, control logic and historical maintenance evidence. Hosamo et al. (2022) proposed a digital twin framework for air handling unit predictive maintenance using BIM, IoT and automatic FDD. Hodavand et al. (2023) reviewed digital-twin applications for building fault detection and diagnosis, noting that data-driven methods are popular because they can process large datasets and adapt to diverse systems. Cespedes-Cubides and colleagues (2024) show that digital twins are increasingly studied for building operations and energy efficiency, although real deployment remains constrained by interoperability and data quality. Mazzetto (2025) argues that hybrid predictive maintenance is especially relevant for buildings because purely data-driven models may be fragile, while purely physics-based models can be expensive to calibrate.

Recent literature also highlights the importance of edge intelligence and water systems. Atanane et al. (2023) showed that TinyML can support low-power water-leak detection in smart buildings. Azam, Shanmugam and Mathur (2023) similarly link IoT and machine learning to water leakage detection. These studies are relevant to Saudi buildings because water security, pumping energy and leakage losses are operational priorities in arid environments. Electrical systems also require predictive attention. Harmonics, transformer temperature, UPS battery health, generator run-hours, power factor, load imbalance and thermal images of panels can all indicate future maintenance needs. Vertical transportation adds another dimension, where door cycles, vibration, motor current and error codes can predict elevator downtime. Therefore, an MEP predictive maintenance framework must cover more than HVAC, even though HVAC usually dominates energy and comfort impacts.

V. CONCEPTUAL FRAMEWORK

The proposed framework treats predictive maintenance as a closed-loop operating system with eight connected layers: asset hierarchy, sensor and IBMS data, data-quality management, AI analytics, risk-based diagnosis, work-order execution, performance verification and continuous learning. Asset hierarchy is the starting point. Every pump, fan, AHU, chiller, cooling tower, VAV box, valve, meter, lift, generator, UPS and water tank should have a consistent tag linked to drawings, O&M manuals, spare parts, warranty conditions and maintenance history. Without this structure, model outputs cannot be translated into accountable work orders. Sensor and IBMS data form the second layer. Required signals include temperatures, pressures, flow rates, vibration, current, voltage, kW, kWh, valve positions, damper positions, filter differential pressure, water quality, tank levels, run-hours, alarms and occupancy indicators.

The data-quality layer checks timestamp alignment, missing values, sensor drift, outliers and impossible states, such as a pump showing zero current while reporting high flow. AI analytics then applies the appropriate modelling method. Time-series models forecast loads and degradation. Classification models detect known fault classes. Unsupervised models identify unusual behaviour when labelled fault data are unavailable. Hybrid models combine physics equations with learned residuals. Digital twins simulate expected behaviour under current weather, occupancy and control settings. The risk-based diagnosis layer converts model outputs into practical decisions. A high probability of filter clogging is not enough; the system should estimate the energy

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penalty, comfort risk, safety impact, spare-part need and recommended intervention date. The work-order layer assigns responsibility and captures technician evidence. The verification layer compares post-maintenance performance against the predicted improvement. The learning layer updates thresholds, retrains models and refines business rules.

This framework is designed for Saudi smart buildings because it aligns technical intelligence with national infrastructure priorities. High temperatures and long cooling seasons increase the importance of HVAC reliability. Large-scale projects require portfolio-level benchmarking. Hospitality, healthcare and airport assets require high comfort and uptime. Mixed-use districts require integration across different occupancy patterns. Predictive maintenance supports these requirements by giving owners early warnings, prioritised work and measurable evidence that maintenance decisions protect both service continuity and energy performance.

VI. MEP PREDICTIVE-MAINTENANCE SCENARIOS

In HVAC systems, the most valuable predictive scenarios include chiller efficiency degradation, refrigerant leakage, condenser fouling, chilled-water valve leakage, AHU filter clogging, fan belt wear, actuator failure, airside imbalance, sensor drift and poor economiser logic. AI models can use kW per ton, chilled-water supply and return temperatures, pressure differentials, outdoor air conditions, compressor cycling, vibration and valve position to identify these conditions. For example, a rising fan kW at constant airflow and increasing filter pressure drop indicates filter loading. If the model also sees lower zone comfort and longer AHU run-time, it can quantify the cost of delayed replacement. Predictive control can then schedule maintenance before peak occupancy or before a heat wave.

In electrical systems, predictive scenarios include transformer overheating, harmonic distortion, power-factor deterioration, UPS battery degradation, generator starting failure, excessive breaker temperature and abnormal load imbalance. These faults are not only electrical risks; they can interrupt HVAC, elevators, life-safety systems and IT services. AI models should therefore combine electrical measurements with dependency mapping. In plumbing systems, predictive scenarios include continuous night flow, tank-level mismatch, pump short-cycling, pressure fluctuation, valve failure, cooling-tower make-up water abnormality and poor water quality. In vertical transportation, predictive scenarios include door motor degradation, abnormal vibration, excessive starts, longer waiting time and fault-code sequences. Across all domains, the maintenance question is not simply whether a fault exists; it is how soon the fault will affect safety, comfort, energy, cost or business continuity.

VII. DATA ARCHITECTURE AND INTEROPERABILITY

A robust architecture is essential because AI models are only as reliable as the data pipeline feeding them. Smart buildings should combine field controllers, BMS/IBMS servers, time-series databases, facility management systems, BIM or digital twin platforms, cybersecurity controls and API-based integration. Open protocols such as BACnet, Modbus, OPC UA and MQTT reduce vendor lock-in, while semantic naming improves model reuse across assets. Data should be logged at frequencies appropriate to the process. Fast control loops may need seconds-level data, while energy and comfort trends may be reliable at fifteen-minute intervals. Cybersecurity must be included from the beginning because connected building systems can expose operational vulnerabilities. Segmented networks, role-based access, encrypted communication, patch management and audit trails are therefore part of maintenance reliability, not separate IT concerns.

Saudi projects also need a clear data ownership model. Owners, operators, consultants, contractors and technology vendors often share responsibility during design, handover and operation. If data rights, model access and performance obligations are unclear, predictive maintenance becomes difficult to sustain. Contracts should define which data are collected, who validates sensors, how long data are retained, how vendors access operational systems, and how model recommendations are reviewed. For high-risk assets, AI outputs should support human decision-making rather than bypass it. A practical approach is to classify predictions into advisory, supervised and automated actions. Advisory outputs inform technicians. Supervised outputs create work orders for approval. Automated outputs adjust non-critical settings when confidence is high and operational constraints are satisfied.

VIII. PROPOSED IMPLEMENTATION METHODOLOGY

The implementation methodology has five phases. Phase one is baseline assessment. It audits asset criticality, maintenance history, sensor readiness, IBMS points, data quality, energy baselines and comfort complaints. The outcome is an AI-readiness score for each MEP asset group. Phase two is instrumentation and data governance. Missing sensors are added only where they support a defined maintenance scenario. Asset tags are standardised, dashboards are simplified and data pipelines are tested. Phase three is fault library development. Engineering teams define expected symptoms, likely root causes, operational consequences and recommended actions for each fault. This library combines manufacturer knowledge, technician experience and literature-based FDD rules.

Phase four is AI model deployment. Models are selected according to data availability and decision need. Rule-based FDD is suitable for simple engineering limits. Isolation Forest, autoencoders or clustering can detect abnormal patterns when labelled data are limited. Random forest, XGBoost, support vector machines and neural networks can classify known faults when labelled examples exist. LSTM or GRU models can forecast loads and degradation in sequential data. Bayesian networks can represent uncertainty and causal relationships. Phase five is continuous commissioning. The system verifies whether maintenance actions actually improved kW/ton, pressure drop, water loss, comfort hours, alarms or downtime. Models are recalibrated when equipment is replaced, control sequences are changed or occupancy patterns shift.

This phased methodology avoids a common mistake: purchasing AI software before defining maintenance decisions. In a Scopus/Q1-style applied review, the priority is not to claim that one algorithm is universally best. The priority is to match algorithms to data maturity, asset criticality, fault type and operational governance. Saudi owners can begin with high-value assets such as chillers, AHUs, pumps, generators and elevators, then scale across portfolios once the data model and work-order process are stable.

IX. EXPECTED PERFORMANCE BENEFITS

AI-based predictive maintenance can deliver five categories of benefits. The first is reliability. Earlier detection of degradation reduces unplanned downtime, emergency callouts and tenant complaints. The second is energy performance. Faults such as clogged filters, leaking valves, poor condenser heat rejection and sensor bias often waste energy before they cause failure. Detecting them early protects energy intensity and supports Saudi sustainability targets. The third is lifecycle cost. Predictive maintenance can extend asset life by avoiding overload, short cycling and unnecessary replacement. The fourth is occupant wellbeing. Better equipment reliability stabilises temperature, humidity, ventilation, lighting and lift availability. The fifth is management transparency. Dashboards can show avoided downtime, verified energy savings, work-order closure quality and asset health trends for executive decision-making.

However, benefits should be measured carefully. Claims of savings are weak unless baselines are normalised for weather, occupancy and operating hours. Recommended KPIs include mean time between failures, mean time to repair, avoided critical alarms, maintenance cost per square metre, energy-use intensity, HVAC kW/ton, AHU fan energy per airflow, percentage of faults detected before complaint, comfort compliance hours, water loss events, elevator availability, and percentage of AI recommendations verified after action. These KPIs convert predictive maintenance from a technology demonstration into a management system.

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X. BARRIERS AND RISK CONTROLS

The first barrier is data quality. Many buildings have incomplete point naming, failed sensors, overridden controls and fragmented maintenance records. The second is model drift. A model trained during one season, tenancy pattern or equipment condition may lose accuracy after retrofits or operational changes. The third is false alarms. Too many low-confidence alerts will cause technicians to ignore the system. The fourth is explainability. Facility managers need clear evidence, not black-box scores. The fifth is cybersecurity, because predictive maintenance requires connected data flows. The sixth is procurement fragmentation. Design consultants, MEP contractors, controls vendors and facility managers may not be contractually aligned around lifecycle performance. The seventh is skills readiness. Technicians must understand not only mechanical symptoms but also data interpretation and digital work-order feedback.

Risk controls should be embedded into the framework. Data validation rules should run continuously. Model outputs should include confidence levels and root-cause evidence. Alerts should be prioritised by asset criticality and operational consequence. Human review should remain mandatory for safety-critical actions. Cybersecurity requirements should follow recognised principles such as network segmentation, least-privilege access and audit logging. Vendor contracts should avoid closed data silos and require exportable histories. Training should combine AI literacy with practical MEP diagnostics so that local facility teams can challenge, improve and trust the system.

XI. DISCUSSION: ALIGNMENT WITH VISION 2030

Predictive maintenance supports Vision 2030 because it improves the productivity of built assets after construction. Saudi Arabia is investing heavily in advanced infrastructure, but national value depends on how these assets perform during decades of operation. AI-enabled MEP maintenance contributes to operational excellence by reducing service interruptions in hospitals, airports, campuses, hotels and mixed-use districts. It also supports sustainability by lowering avoidable energy consumption and water loss. It supports localisation by creating demand for Saudi engineers, technicians and data specialists who understand both digital systems and building services. It supports private-sector competitiveness because reliable buildings reduce tenant disruption and improve asset value.

The strongest opportunity is portfolio intelligence. A single building can identify its own faults, but a portfolio can compare similar assets under different climates, occupancy profiles and maintenance practices. This allows owners of giga-projects and public facilities to identify systemic issues, rank retrofit priorities and standardise best-performing maintenance sequences. Predictive maintenance can therefore become a national infrastructure capability when supported by data standards, skilled facility teams and evidence-based procurement.

A further practical implication is that predictive maintenance should be introduced with patience and discipline. Early pilots should choose assets where technicians already understand failure modes and where sensors are sufficiently reliable. Success should be proven through corrected faults, reduced alarms, verified energy improvement and better occupant response, not through dashboard appearance alone. When teams see that the model helps them solve real problems, adoption becomes easier and resistance decreases. This people-centred pathway is important in Saudi smart buildings because the technology must support daily operation, contractor accountability and long-term knowledge transfer across the local facilities workforce.

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Therefore the framework should remain flexible measurable transparent auditable scalable secure operator friendly climate aware cost conscious and aligned with verified facility performance outcomes. Practically, Saudi operators should treat each prediction as a maintained evidence record, linking sensor trace, model confidence, technician inspection, corrective action, cost, downtime avoided and post-repair performance, so that AI value can be audited across assets, seasons, contractors, and project phases without depending on undocumented assumptions.

XII. CONCLUSION

This review developed an AI-based predictive maintenance framework for MEP systems in smart buildings under Vision 2030. The literature from 2020 to 2025 indicates strong growth in AI-enabled FDD, digital twins, machine learning, predictive control and smart building analytics. Yet the evidence also shows that successful predictive maintenance depends less on isolated algorithms and more on integrated architecture, trusted data, clear asset hierarchy, explainable diagnosis, work-order governance and continuous commissioning. The proposed framework links sensors, IBMS data, digital twins, AI models, risk scoring, technician feedback and KPI verification into a closed-loop lifecycle method. For Saudi Arabia, this approach is especially relevant because high cooling demand, large infrastructure programmes and national sustainability goals require buildings that are reliable, efficient and adaptive. Future research should validate the framework through Saudi case studies, compare algorithm performance across climatic regions, quantify lifecycle cost savings and develop procurement models that reward verified operational outcomes rather than technology installation alone.

Graphical Representations

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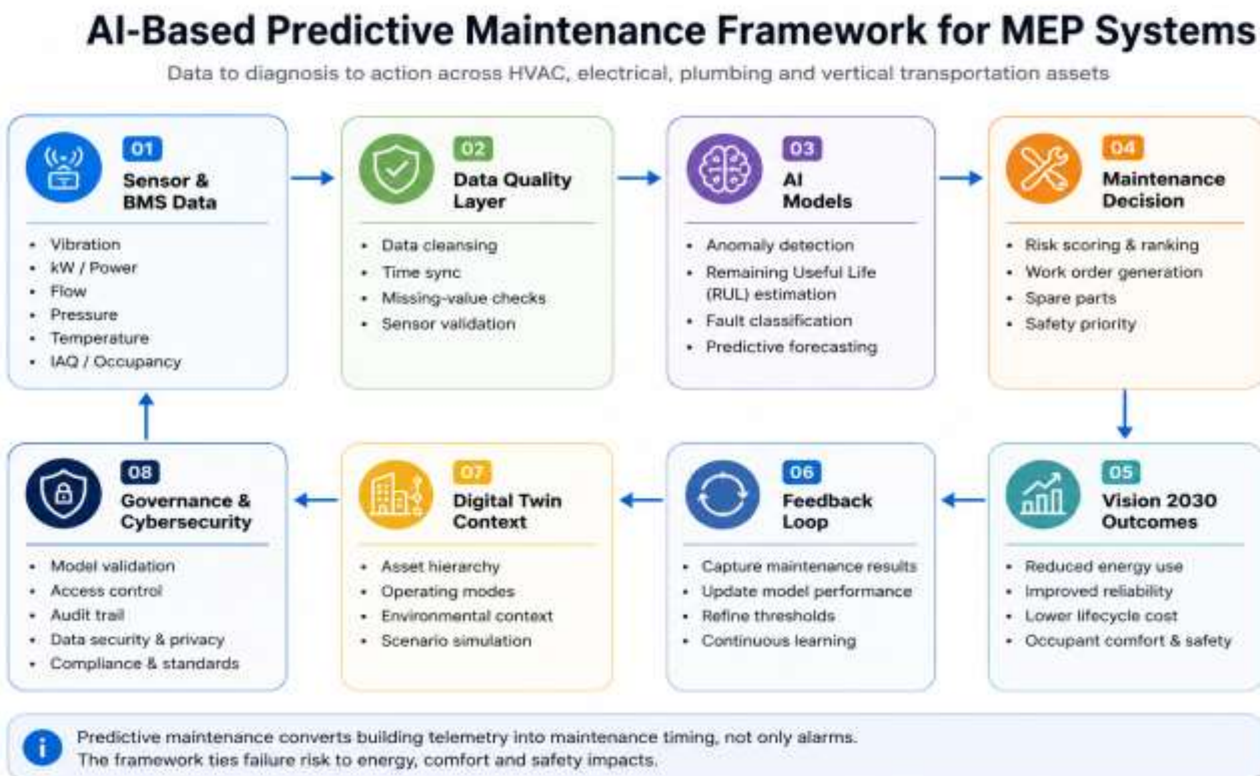

Figure 1. Apple-style conceptual framework linking MEP data, AI analytics and maintenance outcomes.

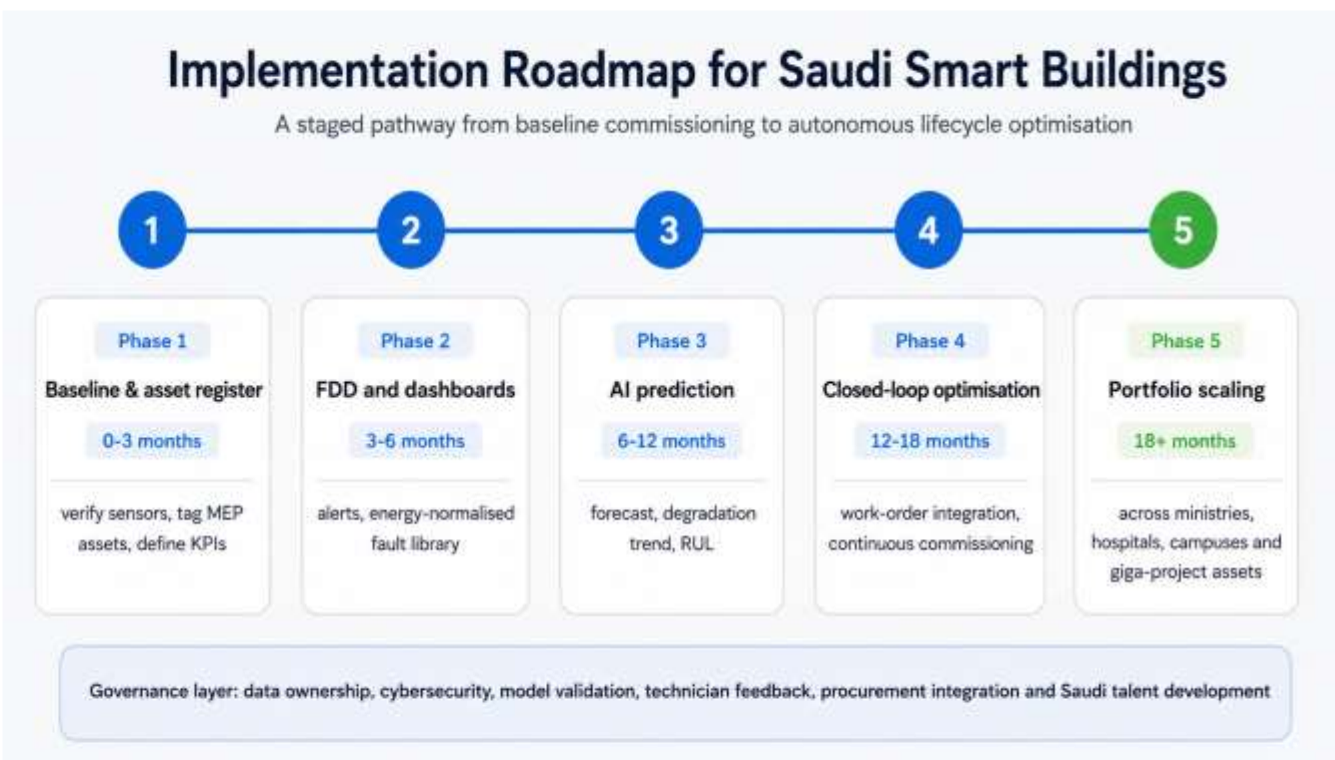

Figure 2. Apple-style implementation roadmap for AI predictive maintenance deployment in Saudi smart buildings.

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Tables

Table 1. Review synthesis matrix for AI-enabled predictive maintenance in MEP smart-building systems.

Theme	Representative evidence	MEP relevance	Saudi Vision 2030 value	Implementation gap
AI/FDD for HVAC	Deep learning and ML studies show improved fault classification and diagnosis (Taheri et al., 2021; Bi et al., 2024).	Chillers, AHUs, VAV boxes, filters, valves and sensors.	Lower energy intensity and fewer comfort complaints.	Need labelled fault data and explainable outputs.
Digital twins	Digital twin studies connect BIM, IoT and maintenance records for asset-level diagnosis (Hosamo et al., 2022; Hodavand et al., 2023).	Asset hierarchy, live sensor streams and simulated expected behaviour.	Useful for giga-project portfolios and lifecycle governance.	Interoperability, model calibration and contract ownership remain difficult.
Predictive control	MPC and energy modelling optimise HVAC operation using weather, occupancy and constraints (Drgoňa et al., 2020; Kim et al., 2022).	Pre-cooling, load shifting, ventilation and setpoint management.	Supports demand management and efficiency targets.	Requires commissioning discipline and stable control sequences.
Water and plumbing analytics	TinyML and IoT leakage research enables low-power abnormal-flow detection (Atanane et al., 2023; Azam et al., 2023).	Pumps, tanks, risers, cooling-tower make-up and pressure networks.	Water stewardship for arid-region facilities.	Fault taxonomies are less mature than HVAC.
Governance and asset management	Asset-management standards emphasise lifecycle value and evidence-based decisions (ISO, 2024).	Work orders, spare parts, risk ranking and verification.	Develops local facility-management capability.	AI recommendations must be integrated into technician workflows.

Table 2. Proposed MEP predictive-maintenance data points, models and performance indicators.

MEP asset	Critical data points	Predictive method	Failure signal	Recommended action	KPI
Chiller/VRF plant	kW/TR, suction/discharge pressure, CHW temperature, alarms, run-hours	Hybrid FDD, regression, LSTM	Efficiency degradation, refrigerant issue, fouling	Inspect condenser, recalibrate sensor, schedule service	kW/TR; avoided downtime
AHU and fans	Filter pressure, fan kW, airflow, vibration, damper position	Anomaly detection, classification	Filter clogging, belt wear, damper fault	Replace filter, balance air, repair actuator	Fan energy; comfort hours
Pumps and plumbing	Flow, pressure, current, tank level, night flow, TDS/pH	Time-series anomaly detection	Leakage, cavitation, valve failure	Leak inspection, valve repair, pump service	Water loss; pump availability
Electrical	Voltage, current,	Trend analysis,	Overheating,	Thermal scan, load	Electrical

systems	harmonics, temperature, UPS battery, DG fuel/run-hours	Bayesian risk model	battery degradation, load imbalance	redistribution, battery replacement	availability; alarms
Lifts	Door cycles, vibration, motor current, fault codes, wait time	Sequence mining, classification	Door mechanism wear, drive anomaly	Schedule lift contractor intervention	Availability; complaint rate

REFERENCES

[1] Adhikari, A., Koronios, A. and Aouad, G. (2025), 'Machine learning for predictive maintenance in building services: a semi-systematic review', Facilities, 43(5/6), pp. 469-492.

[2] Aghili, S.A., et al. (2025), 'Artificial intelligence approaches to energy management in HVAC systems in buildings: a systematic review', Buildings, 15(7), 1008.

[3] ASHRAE (2020), Guideline 36-2020: High-Performance Sequences of Operation for HVAC Systems, ASHRAE, Atlanta.

[4] Atanane, O., Mourhir, A., Benamar, N. and Zennaro, M. (2023), 'Smart buildings: water leakage detection using TinyML', Sensors, 23(22), 9210.

[5] Azam, S., Shanmugam, B. and Mathur, D. (2023), 'An intelligent IoT and machine-learning based water leakage detection system', IEEE Access, 11, pp. 108263-108278.

[6] Bi, J., et al. (2024), 'Artificial intelligence in HVAC fault detection and diagnosis: a systematic review', Energy Reviews, 3, 100071.

[7] Cespedes-Cubides, A.S., et al. (2024), 'A review of building digital twins to improve energy efficiency in the building operational stage', Smart Cities, 7(4), pp. 1830-1865.

[8] Chen, Y., et al. (2021), 'Multi-objective optimisation of building comfort and energy use through predictive control', Energy Efficiency, 14, 52.

[9] Drgoňa, J., Arroyo, J., Cupeiro Figueroa, I., Blum, D., Arendt, K., Kim, D., Ollé, E.P., Oravec, J., Wetter, M., Vrabie, D.L. and Helsen, L. (2020), 'All you need to know about model predictive control for buildings', Annual Reviews in Control, 50, pp. 190-232.

[10] Es-Sakali, N., Cherkaoui, M. and Rachik, M. (2022), 'Review of predictive maintenance algorithms applied to HVAC systems', IFAC-PapersOnLine, 55(10), pp. 1576-1581.

[11] Guo, Y., Wang, Y., Xue, P. and Guo, Y. (2024), 'Advance and prospect of machine learning based fault detection and diagnosis in air-conditioning systems', Renewable and Sustainable Energy Reviews, 205, 114849.

[12] Haruehansapong, K., et al. (2022), 'Deep learning-driven automated fault detection and diagnostics for HVAC systems', Buildings, 13(1), 27.

[13] Hodavand, F., et al. (2023), 'Digital twin for fault detection and diagnosis of building operation and maintenance: a systematic review', Buildings, 13(6), 1426.

[14] Hosamo, H., Svennevig, P.R., Svidt, K., Han, D. and Nielsen, H.K. (2022), 'A digital twin predictive maintenance framework of air handling units based on automatic fault detection and diagnostics', Energy and Buildings, 261, 111988.

[15] IEA (2023), Energy Efficiency 2023, International Energy Agency, Paris.

[16] IEA (2025), Energy Efficiency 2025: Buildings, International Energy Agency, Paris.

[17] ISO (2024), ISO 55001:2024 Asset Management - Asset Management System Requirements, International Organization for Standardization, Geneva.

[18] Kim, D., Cai, J., Ariyur, K.B. and Braun, J.E. (2022), 'Energy modeling and model predictive control for HVAC in buildings: a review', Energies, 15(19), 7231.

[19] Kumar, S., et al. (2021), 'Privacy-preserving occupancy detection for energy-efficient buildings using federated learning', Energy Reports, 7, pp. 6305-6318.

[20] Li, G., et al. (2021), 'An explainable one-dimensional convolutional neural networks based fault diagnosis method for building HVAC systems', Building and Environment, 203, 108057.

[21] Mazzetto, S. (2025), 'Hybrid predictive maintenance for building systems: state of the art and future directions', Buildings, 15(4), 630.

[22] Saudi Building Code National Committee (2021), Saudi Building Code: Energy Conservation Requirements, Riyadh.

[23] Saudi Green Initiative (2024), Reducing Carbon Emissions, Saudi Green Initiative, Riyadh.

[24] Saudi Vision 2030 (2024), Vision 2030: An Ambitious Nation and a Thriving Economy, Government of Saudi Arabia, Riyadh.

[25] Taheri, S., Ahmadi, A., Mohammadi-Ivatloo, B. and Asadi, S. (2021), 'Fault detection diagnostic for HVAC systems via deep learning algorithms', Energy and Buildings, 250, 111275.

[26] UNEP and GlobalABC (2024), Global Status Report for Buildings and Construction 2023, United Nations Environment Programme, Nairobi.

[27] UNEP and GlobalABC (2025), Global Status Report for Buildings and Construction 2024/2025, United Nations Environment Programme, Nairobi.

[28] Walther, K., et al. (2025), 'Controls of HVAC systems in digital twins: performance gaps and opportunities', Journal of Building Performance Simulation, 18(2), pp. 141-160.

[29] Zanetti, E., et al. (2023), 'Performance comparison of quadratic, nonlinear and data-driven model predictive control for building HVAC systems', Journal of Building Performance Simulation, 16(4), pp. 432-449.

[30] Zhang, X., et al. (2022), 'Context-aware energy management in smart buildings: machine learning and occupant-centred control', Energy and Buildings, 260, 111895.